EPtask: Deep Reinforcement Learning Based Energy-E fficientand Priority-Aware Task Scheduling for Dynamic Vehicular Edge Computing

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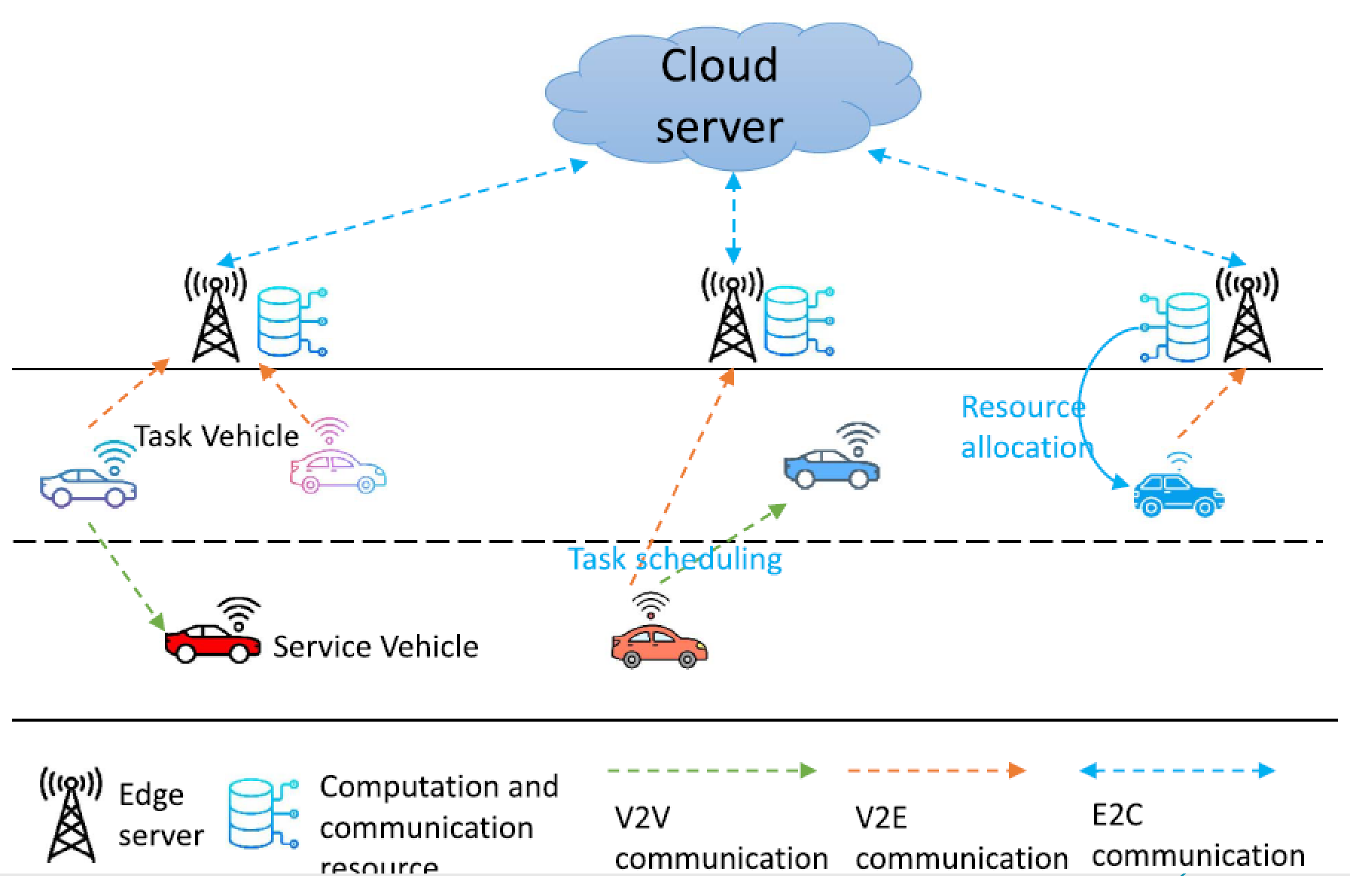


Cloud server
Task Vehicle
Resource allocation
Task scheduling
Service Vehicle
Edge server
Computation and communication resource
V2V communication
V2E communication
E2C communication

VEC

EPTask on VEC: PPO vs. DDPG/SAC & Baselines

- **Goal:** Priority-aware, energy-efficient task scheduling in **Vehicular Edge Computing (VEC)**
- **What we built:** A paper-aligned simulator + RL scheduler (PPO) with suggested baselines (SAC, DDPG, heuristic, local-only, offloading-only, random)
- **Key metrics:** deadline miss rate, completion time, mean energy, throughput.
- **Takeaway:** PPO learns smarter offloading & prioritization under mobility, deadlines, and energy limits.

Problem & Project Objectives

- **Challenge:** Where to compute each task (local/V2V/edge/cloud) and at what priority, under deadlines, mobility, and limited bandwidth/energy
- **Project objectives:**
  - Implement EPTask-style environment
  - Train PPO and compare against DDPG, SAC, heuristic, local-only, offloading-only, random
  - Report miss rate, completion time, energy, throughput
  - show scalability vs. #vehicles
- **Design constraints (per proposal & our choices):**
  - Non-preemptive + EDF
  - Distance-based TX power by default (learned-power kept for ablations).

Paper Alignment & Assumptions

- **Table III mapping (core params):**
    - **Radio:** V2I 100 MHz; noise ≈ −95 dBm (from −174 dBm/Hz over 100 MHz); vehicle TX ≈ 1 dBm (bins for tiers).
    - **Compute:** vehicle ≈ 1 GHz, edge ≈ 2 GHz, cloud ≈ 5 GHz (MIPS equivalents).
    - **Tasks:** size 2–20 Mb, cycles 2–20 × 10^9, 4 priority levels; **Poisson** arrivals (bursty).
- **Mobility & links:** 1-D movement; distance→SNR→rate
- **Scheduling rule: EDF**
- **Energy model:** TX + compute energy per task

TABLE III
EXPERIMENTAL PARAMETERS

Parameters	Value
Number of vehicles	10-50
Number of edge servers	8
Number of tasks	0-10
Required CPU cycles of the tasks C	2-20 cpu cycles
Computation power of edge servers	2 cpu cycles/s
Computation power of vehicles	1 cpu cycles/s
data size S	2-20 Mb
Bandwidth of edge server	100 MHz
Speed of vehicles	$\approx$ 25 m/s
Transmit power of vehicles	1 dBm
Execution power of vehicles	3-4 dBm
White Gaussian noise	-174 dBm/Hz
Power consumption coefficient ξ	10^{-11}
Power consumption coefficient γ	2
Received Signal Strength Indicator $RSSI$	-65 dBm
Transmit antenna gain TX	20 dBi
Receive antenna gain RX	-8 dBi
Signal attenuation SA	7 dB
Working frequency f	5GHz
Learning rate	0.0003
Size of Mini-batch	32
Number of steps in each episode	2048
Entropy loss coefficient	0.01

Simulator Architecture (What’s in Code)

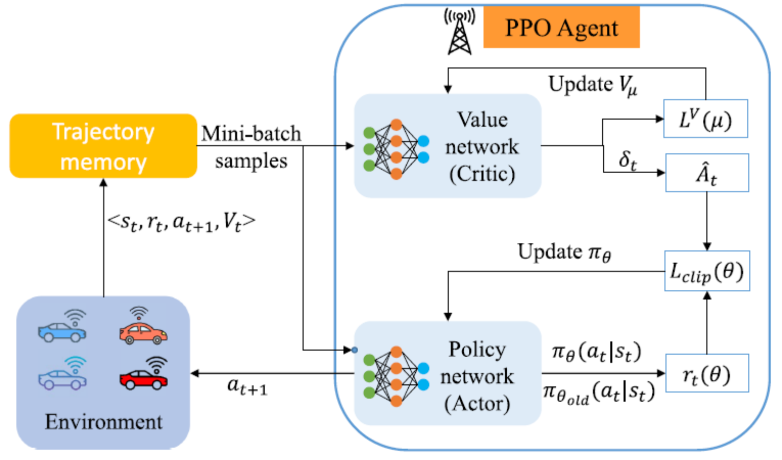
- **Env core (env/vec_env.py):**
  - Builds **Dict observation** (global/task/target/vehicle tensors)
  - **Action** per step on top-K tasks: *(offload target, priority)*
  - **Task generation:** Poisson arrivals; sample_tasks() from env/generators.py
  - **Link budget:** distance→SNR→rate
  - **Energy/time:** env/models.py (tx/compute time + energy functions)
  - **Reward:** −(z-time + z-energy) − λ·misses

- **Metrics & tools:**
  •env/metrics.py, scripts/eval_metrics.py, scripts/plot_metrics.py.
  •Grid & scalability: scripts/run_grid.py, scripts/plot_vs_vehicles.py.

RL Formulation & Methods

- **Action (per top-K tasks):**
  - **Offload target** ∈ {local, vehicles, edges, cloud}
  - **Priority level** ∈ {1..4}
  - *(default is distance-based, no power head)*
- **Reward:**
  - (λ_1·**z(completion time)** + λ_2·**z(energy)**) − λ_3·**#deadline_misses** (per step)

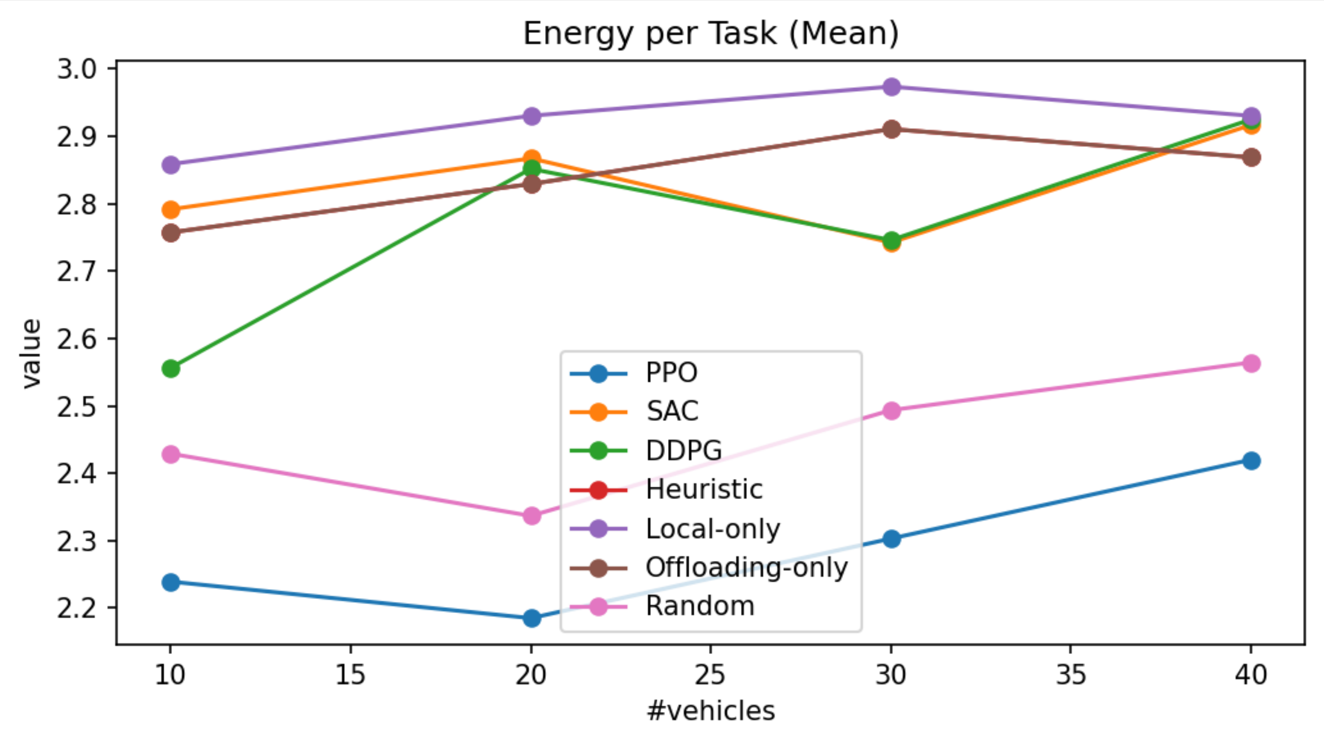
- **Training setup:** horizon 600; n_steps=2048, lr=3e-4; eval on 5 episodes;



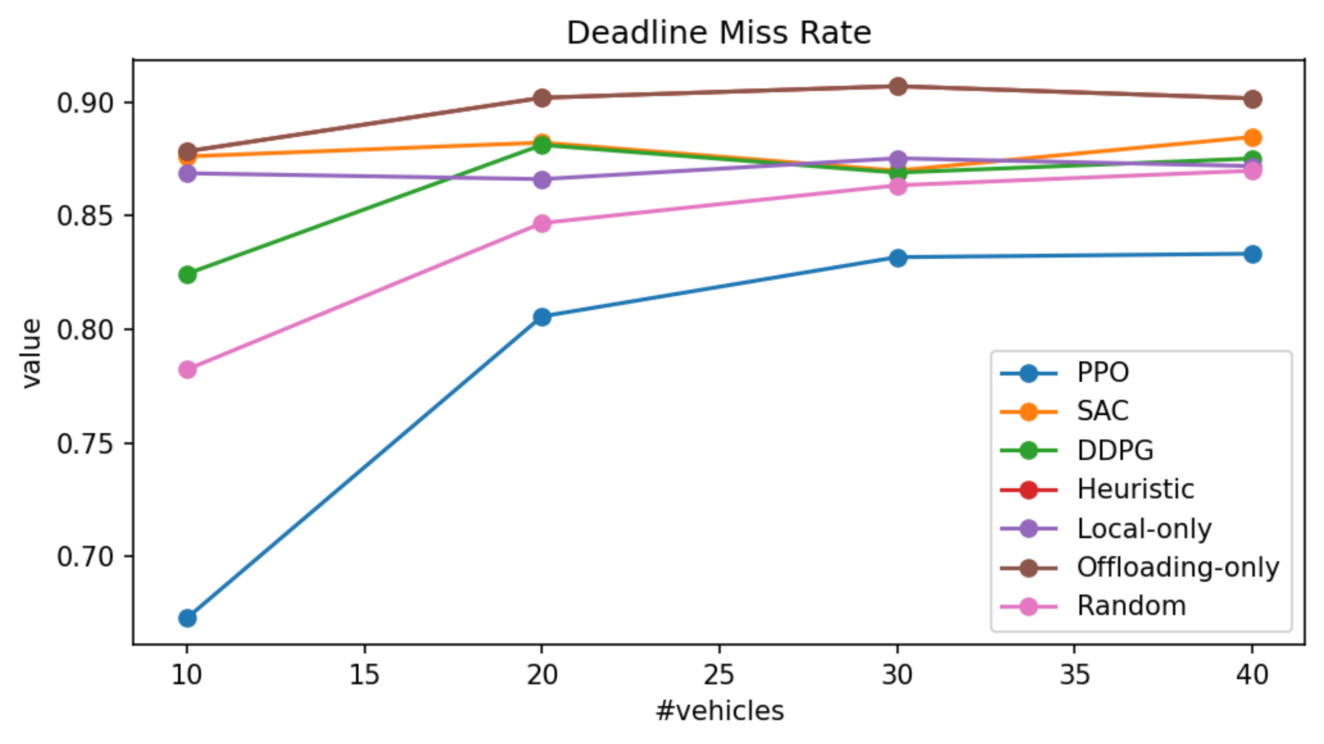
Results

- **Setup:** configs/default.yaml, horizon 600, Poisson arrivals, distance-based power
- **Key findings (qualitative):**
  - **PPO** achieves the **lowest deadline miss rate**
  - Energy per task stays competitive with SAC/DDPG and lower than fixed baselines at load
- **Why:** PPO’s discrete offload + priority decisions adapt to bursty queues and mobility.

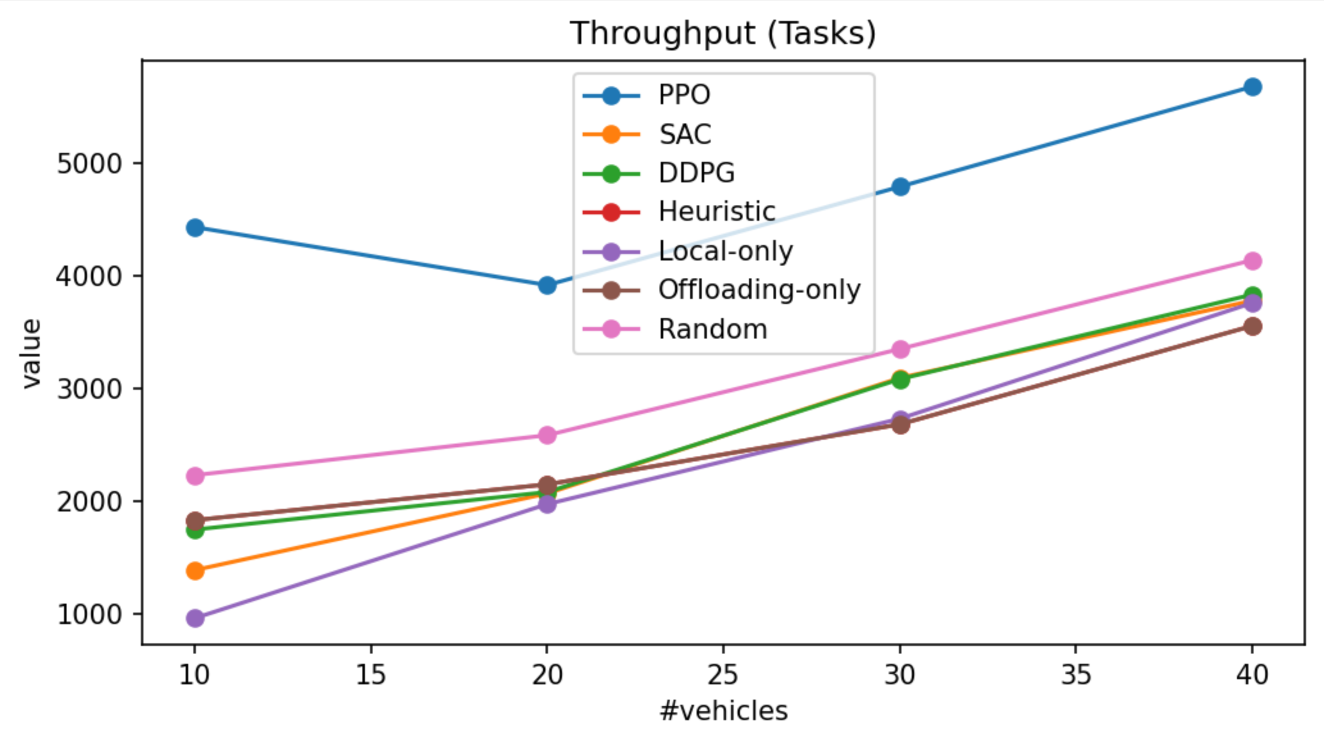
Energy per Task Comparison



Deadline Miss Rate Comparison



Throughput Comparison



Scalability vs #Vehicles

- **Experiment:** $V \in \{10, 20, 30, 40, 50\}$, seeds = $\{0,1,2\}$, 5 eval episodes each.
- **Trend highlights:**
  - As **vehicles↑**, **offloading-only** degrades (shared V2I), **local-only** saturates on compute
  - **PPO** maintains **lower miss rate** by balancing local/V2V/edge/cloud
  - Throughput grows with V
- **Interpretation:** Learning when **not** to offload is as important as offloading

Insights

- **Distance-based power (default) vs learned power (ablation):**
  - Removing the power head shrinks the action space → faster, stabler PPO
- **No-V2V ablation:**
  - Increases queueing at edges/cloud
- **Heuristic (EDF + min-ETA):**
  - Strong at light load; under bursty arrivals and higher V, it misjudges congestion vs PPO
- **Reward normalization (running z-scores):**
  - Critical for stable training on CPU (prevents advantage blow-ups)
- **Takeaway:** The **offload+priority** structure is the main win

Reproducibility & Engineering

- **One-command pipelines**
  - **Train:** scripts/train.py, train_sac.py, train_ddpg.py
  - **Evaluate & metrics:** scripts/eval_metrics.py
  - **Baselines:** scripts/baseline_heuristic.py --mode {heuristic,local,offload,random}
  - **Grids & plots:** scripts/run_grid.py, scripts/plot_metrics.py, scripts/plot_vs_vehicles.py
- **Configs & seeds**
  - YAML configs (Table-III aligned); **config snapshot** saved in each logdir.
  - Multi-seed runs (≥3) aggregated to mean±std tables/plots.
- **Environment**
  - Gymnasium env, Dict observations

Any Questions?

References

1. P. Li, Z. Xiao, X. Wang, K. Huang, Y. Huang and H. Gao, "EPtask: Deep Reinforcement Learning Based Energy-Efficient and Priority-Aware Task Scheduling for Dynamic Vehicular Edge Computing," in IEEE Transactions on Intelligent Vehicles, vol. 9, no. 1, pp. 1830-1846, Jan. 2024, doi: 10.1109/TIV.2023.3321679.