A Deep Ensemble Method for Multi-Agent Reinforcement Learning: A Case Study on Air Traffic Control

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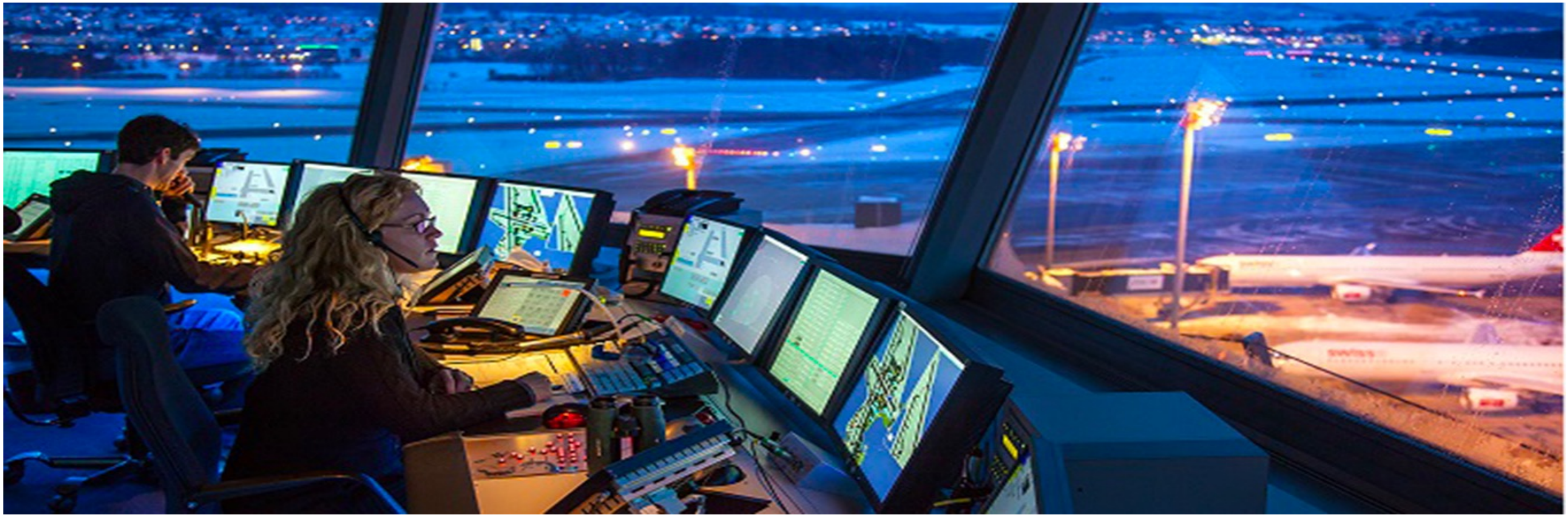
Motivation

- **Air traffic control (ATC)**
  - Monitor current state of aircrafts and recommend **real-time** decisions.
  - Need to optimize a complex objective function
    - Minimize congestion, conflicts, arrival delay and fuel consumption cost.
  - Heavy traffic volume might lead to (human) operational errors.
  - A **sequential decision-making** problem involving **multiple actors** influencing each other.



Our Contributions

- Modelled ATC problem within a multi-agent reinforcement learning (MARL) framework.

- Solved the MARL problem with a model-based Kernel RL and a model-free Deep RL methods.

- Proposed a **general-purpose** novel deep ensemble MARL method to combine the power of deep RL and kernel RL.

- Demonstrated the efficacy of ensemble MARL method on a **real-world dataset** consisting of ~1600 active aircrafts.

Multi-agent Reinforcement Learning (MARL)

- Single Agent RL:

$$< \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma >$$

- Learn a policy π to maximize long term reward $Q^*(s,a)$:

$$\mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) | s_0 = s, a_0 = a \right]$$

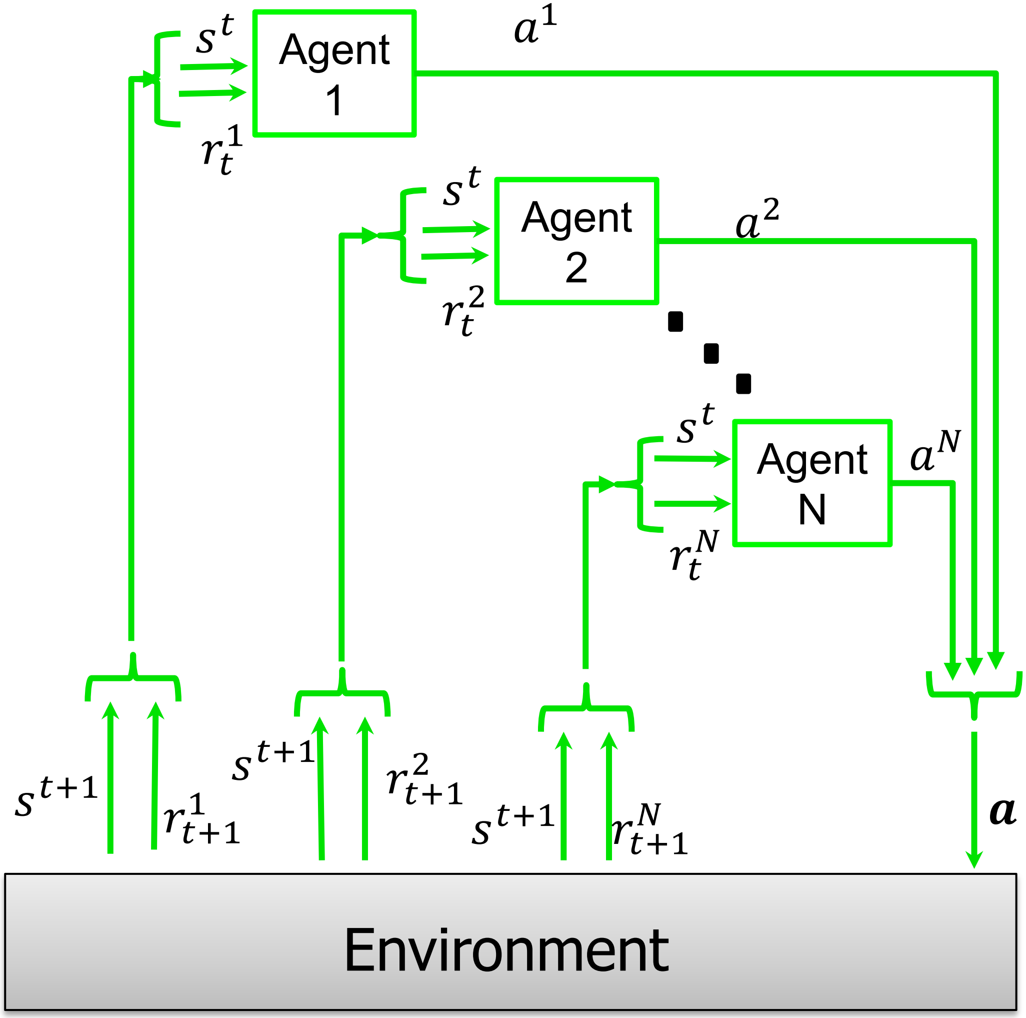
- Multi-agent RL

$$< \mathcal{S}, \underbrace{\mathcal{O}_1 ... \mathcal{O}_N}, \underbrace{\mathcal{A}_1 ... \mathcal{A}_N}, \mathcal{P}, \mathcal{R}, \gamma >$$

Observation: $o_i : \mathcal{S} \rightarrow \mathcal{O}_i$

Transition: $\mathcal{P} : \mathcal{S} \times \mathcal{A}_1 \times ... \mathcal{A}_N \rightarrow \mathcal{S}$

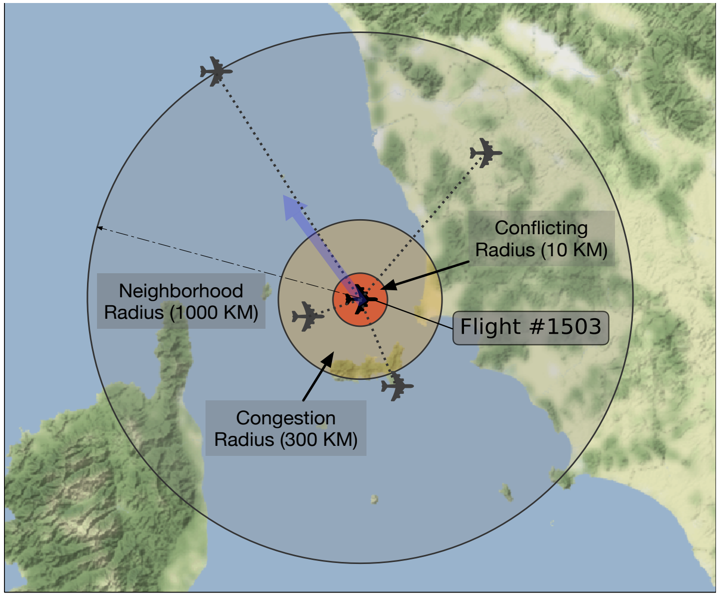
Reward: $r_i : \mathcal{O}_i \times \mathcal{A}_i \rightarrow \mathbb{R}$



Centralized learning & decentralized execution in MARL [Gupta *et. al.*, 2017]

MARL Formulation for ATC

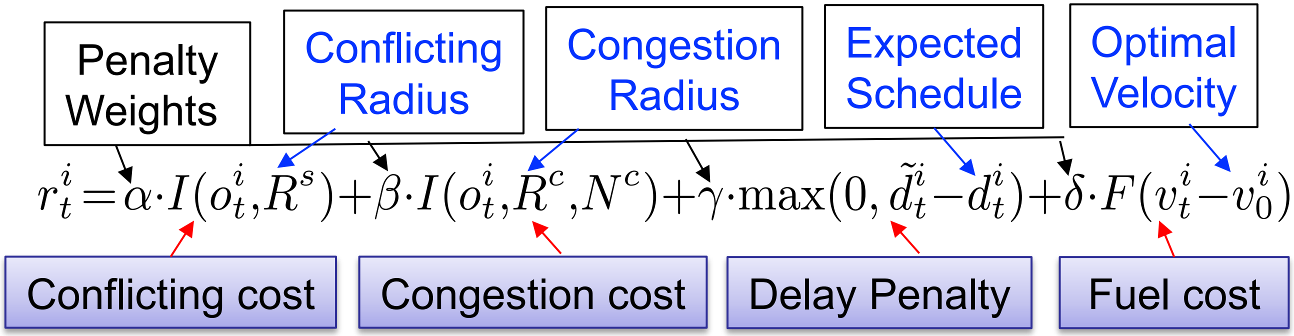
- **State space**
  - Local features: Aircraft's location, speed, direction, timeliness
  - Neighborhood features: N nearest aircrafts' relative velocity & direction
  - Extended feature: Coarse and fine grid image information (for deep RL)


Conflicting Radius (10 KM)
Neighborhood Radius (1000 KM)
Flight #1503
Congestion Radius (300 KM)

- **Action space (deviate speed by δ)**

$$A_t = \{\underbrace{\max(v_{min}, (v_{t-1} - \delta))}, v_{t-1}, \underbrace{\min(v_{max}, (v_{t-1} + \delta))}\}$$

- **Reward Function**



Penalty Weights

Conflicting Radius

Congestion Radius

Expected Schedule

Optimal Velocity

$$r_t^i = \alpha \cdot I(o_t^i, R^s) + \beta \cdot I(o_t^i, R^c, N^c) + \gamma \cdot \max(0, \tilde{d}_t^i - d_t^i) + \delta \cdot F(v_t^i - v_0^i)$$

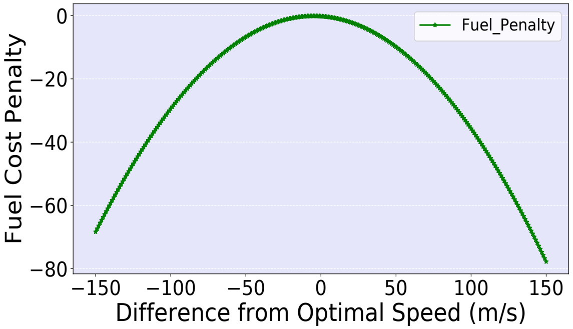
Conflicting cost

Congestion cost

Delay Penalty

Fuel cost

Fuel cost penalty structure



Kernel and Deep MARL for ATC

Model based kernel RL

1. Inputs: $S^a = \{s_k^a, r_k^a, \hat{s}_k^a | k = 1, \ldots, n_a\} \forall a \in \mathcal{A}$
2. Generate m representative states with K-means clustering: $\bar{S} = \{\bar{s}_1, \ldots, \bar{s}_m\}$
3. Define Gaussian kernel κ_τ, $\bar{\kappa}_{\bar{\tau}}$ using distance from original to representative state
4. Compute $D^a : d_{ij}^a = \bar{\kappa}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_j)$
5. Compute $K^a : k_{ij}^a = \kappa_\tau^a(\bar{s}_i, s_j^a)$
6. Compute transition probability: $P^a = K^a D^a$
7. Compute reward $r^a : r_i^a = \sum k_{ij}^a r_j^a$
8. Solve MDP$\{\bar{S}, \mathcal{A}, P^a, r^a, \gamma = .99\}$ & obtain Q^*

- **Advantages**
  - Performs well in neighborhood of dense training
  - Strong theoretical bounds
- **Limitations**
  - Extrapolates poorly

Model free deep RL (PPO)

1. Initialize policy network with parameter θ_0
2. For each episode k, store a set of transition samples $(s_t^i, a_t^i, r_t^i, s_{t+1}^i)$ for each agent i in buffer D by simulating policy $\pi(\theta_k)$
3. Update θ_k with minibatch of transitions from D for M rounds to optimize PPO objective:

$$\mathbb{E}_t\left[\min(r_t(\theta)A_t, clip(r_t(\theta),1-\epsilon,1+\epsilon)A_t)\right]$$

$r_t(\theta)$ is ratio between $\pi_\theta(a_t|s_t)$, $\pi_{\theta_{old}}(a_t|s_t)$

$A_t := R_t - V(s_t)$ is advantage function

- **Advantages**
  - Flexible and generalizes well
  - Can deal with richer state space
- **Limitations**
  - Can be brittle even in dense training neighborhood

Deep Ensemble MARL

- Existing ensemble methods are either not feasible for model-based methods or unable to take multi-agent interactions in account.
- We *train a separate deep neural network* that efficiently learns to arbitrate between decisions of **pre-trained** kernel and deep MARL.

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Inputs: Kernel model $\widetilde{K}$, PPO model $\tilde{\pi}(\tilde{\theta})$
1. Initialize ensemble policy to $\pi(\theta_0)$
2. For each episode $k$, run line 3-7
3. For each time $t$ and agent $i$, sample ensemble action $a_t^i$ for observation $s_t^i$
4. If $a_t^i$ is 0 then get action $\tilde{a}_t^i$ from $\widetilde{K}$, otherwise get $\tilde{a}_t^i$ using $\tilde{\pi}(\tilde{\theta})$
5. Execute joint action $\tilde{\boldsymbol{a}}_t = (\tilde{a}_t^1, \dots, \tilde{a}_t^{N_t})$
6. Store transitions $(s_t^i, a_t^i, r_t^i, s_{t+1}^i)$ in $D$
7. For M rounds update $\theta_k$ with minibatch of transitions from $D$
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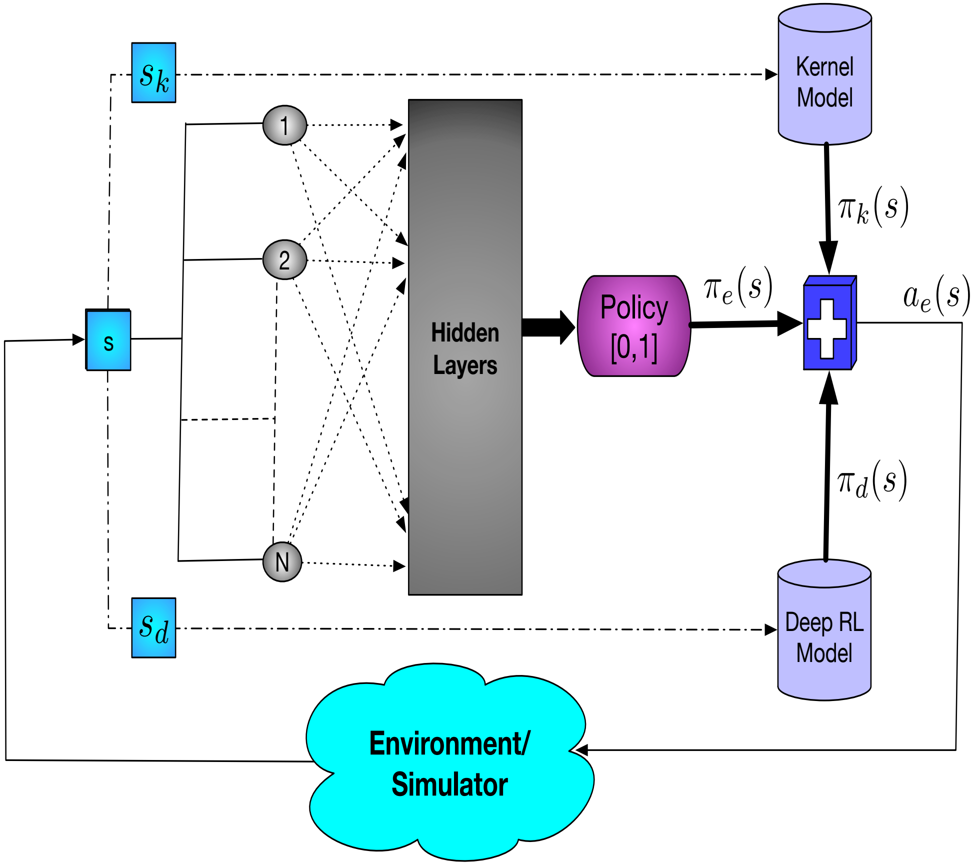
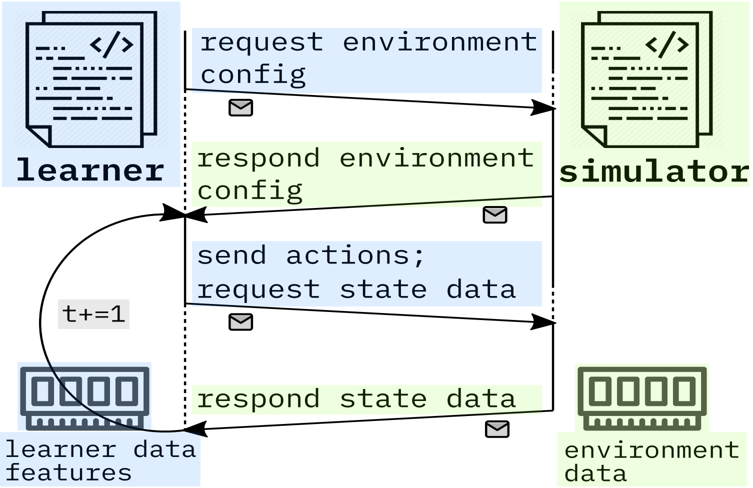


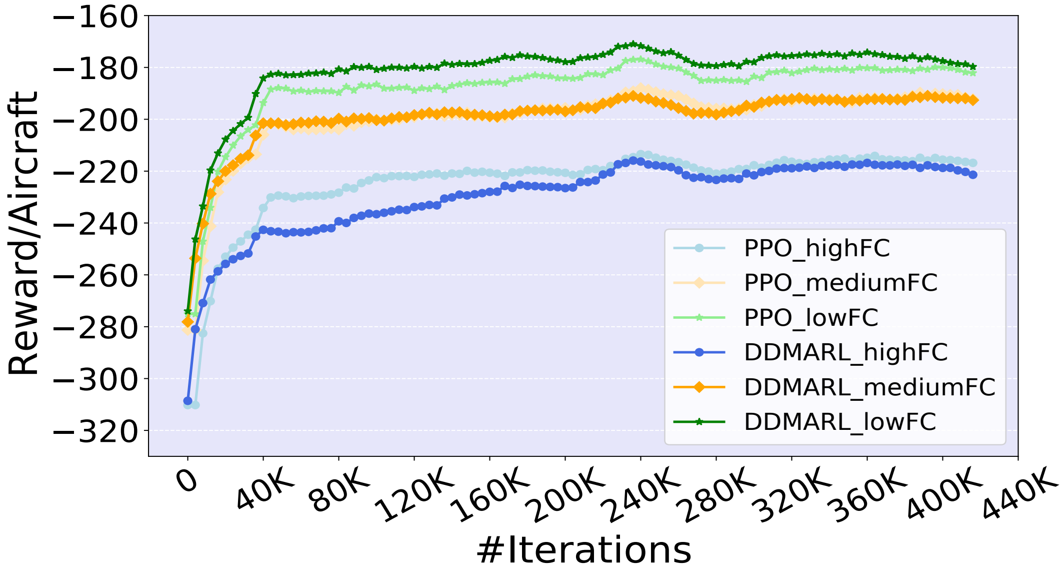
Experimental Settings

- **Datasets (from Southern Europe)**
  - 24-hours schedule for 1600 active flights
  - 300 training days and 30 testing days
  - 3 fuel cost settings considered: low, medium (from Airbus), high
- **Benchmark Approaches**
  - Baseline: simulate default schedule (no penalty for fuel & delay)
  - Local search: Each aircraft chooses a myopic best action
  - DDMARL (Brittain et. al., 2019): Only consider conflict penalty
- **Air traffic simulator**
  - An open-source simulator developed by **Eurocontrol**
  - We develop a message passing adapter between the simulator and our RL agent

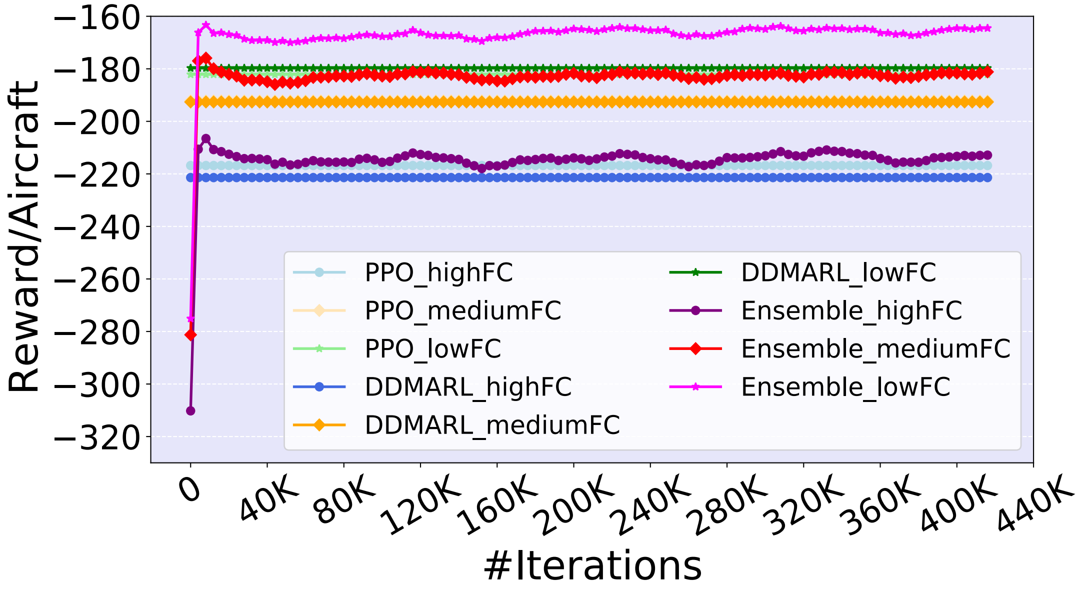

learner
request environment config
simulator
respond environment config
send actions; request state data
t+=1
respond state data
learner data features
environment data

Training Performance

- Training performance of our deep MARL is at par with DDMARL

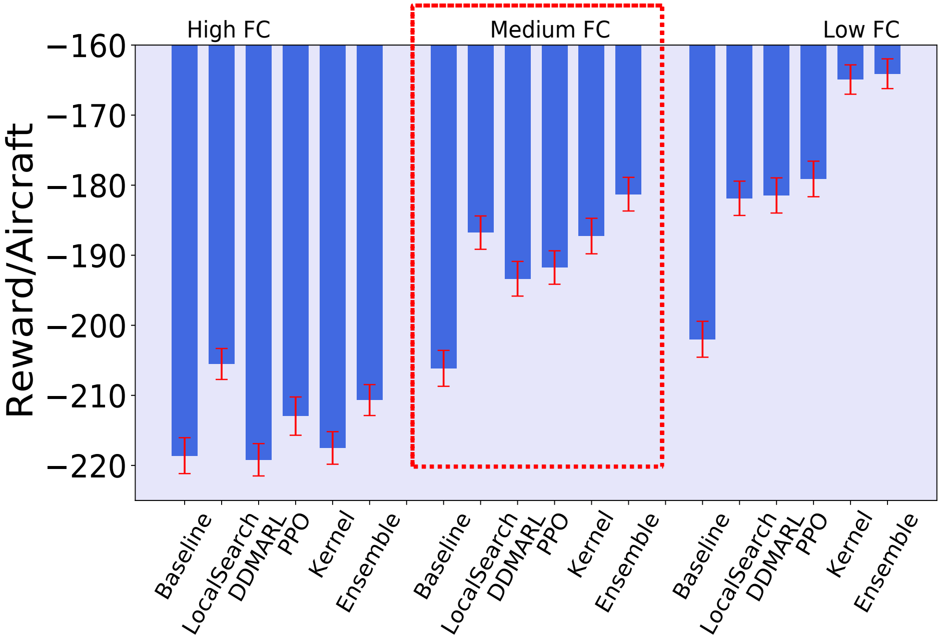


- Our ensemble MARL has better training performance than both deep MARL and DDMARL across the board

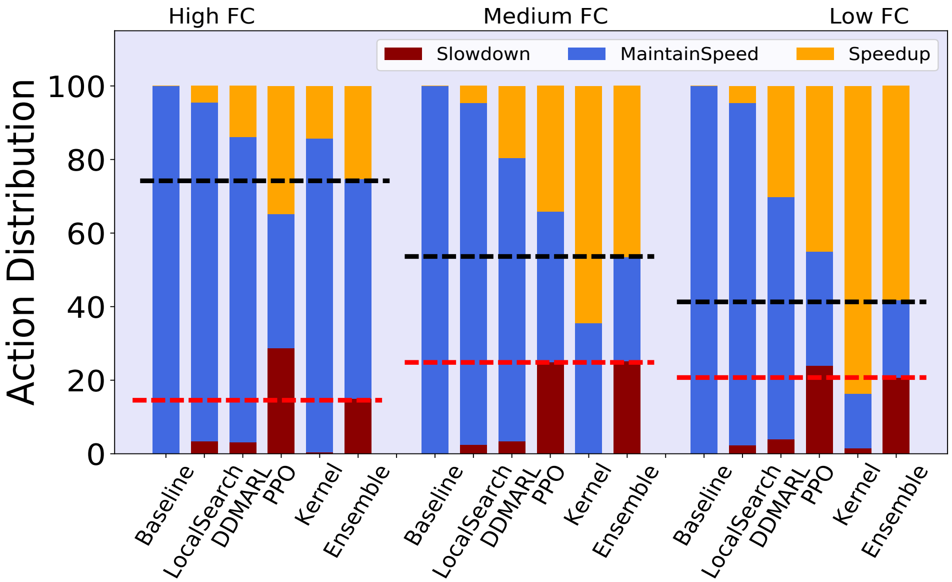


Testing Performance

- Ensemble MARL always out-performs kernel and deep RL.
- Ensemble MARL provides ~9% gain in reward in a realistic fuel cost setting.



- Benchmark approaches have skewed action distribution.
- Ensemble MARL diversifies actions to maximize overall reward value.



Conclusion

- **Summary:**
  - We formulated the ATC problem using MARL framework.
  - Proposed **a novel deep ensemble MARL** method to combine the power of a model-based kernel RL and model-free deep RL.
  - Ensemble MARL method **improves the ATC objective by 9%** over existing benchmarks on a real-world dataset.

- **Future Directions:**
  - Extend action space to incorporate additional controls such as directional and altitude changes.
  - Extend state space to handle take-off and landing scenarios.
  - Extend ensemble MARL to combine power of multiple methods.