Airline Integrated Scheduling: MA-HRL Architecture + Topology-GRPO Algorithm

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***Abstract*—This paper proposes a complete solution for airline integrated scheduling based on the Multi-Agent Hierarchical Reinforcement Learning (MA-HRL) architecture and the Topology-Graph Relative Policy Optimization (Topology-GRPO) algorithm. The solution adopts a hierarchical multi-agent collaboration and global coordination design, which aligns with airline scheduling decision logic, balances safety constraints and global optimization objectives, and achieves efficient, stable, and compliant scheduling in complex scenarios.**

***Index Terms*—Airline scheduling; multi-agent reinforcement learning; MA-HRL; Topology-GRPO; intelligent decision-making**

I. MA-HRL Architecture for Airline Integrated Scheduling

The architecture follows a hierarchical multi-agent collaboration and global coordination paradigm, matching real-world airline scheduling decision hierarchies. It ensures hard safety constraints and global optimization goals. Data flows unidirectionally between layers, and peer agents communicate in a distributed manner.

A. Overall Architecture Topology

The MA-HRL framework consists of four layers: global coordination agent, middle-layer multi-agent cluster, hard-constraint execution filter, and environment and data perception layer.

B. Core Functions of Each Layer

1) Global Coordination Agent: As the sole top-level decision-making unit, it does not execute low-level actions. It outputs global optimization objectives, cross-agent resource quotas, and conflict coordination rules, balancing on-time performance, operational cost, and passenger experience.

2) Middle-Layer Multi-Agent Cluster: Four parallel agents make independent decisions and communicate locally:

- **Flight Scheduling Agent**: Adjusts timetables, matches aircraft types, optimizes flight strings.
- **Fleet Scheduling Agent**: Manages aircraft rotations, inserts maintenance windows, allocates fleet resources.
- **Crew Scheduling Agent**: Performs crew pairing, controls duty time, ensures rest compliance.
- **Flight Recovery Agent**: Handles emergency rescheduling under disruptions, controls secondary delays.

3) Hard-Constraint Execution Filter Layer: Uses action masking and penalty mechanisms to rigidly block violations of civil aviation regulations, flight hours, maintenance airworthiness, and airport time windows.

4) Environment and Data Perception Layer: Integrates flight operations, fleet status, crew information, weather, flow control, and airport congestion data to provide standardized state inputs.

II. Topology-GRPO for Airline Scheduling

Based on MA-HRL, agent scheduling relationships are transformed into a dynamic directed graph to reduce communication redundancy and state-space explosion.

A. Formal Definition of Topology Graph

Define the scheduling graph $G = (V, E, S)$:

- $V = \{V_f, V_p, V_c, V_r\}$: Flight, Fleet, Crew, Recovery agents.
- $E_{ij} \in \{0, 1\}$: Communication edges; dynamically learned.
- S: Global state including flight plans, fleet position, crew duty, weather, slots, transfers.

B. Topology Generation Rules

1) Generate node embeddings via Graph Attention Network (GAT).
2) Keep top-K weighted edges to ensure sparsity.
3) Expand local edges in emergencies; maintain minimal topology in normal operations.

III. Core Algorithm Pseudocode

The Topology-GRPO algorithm uses a critic-free, grouped relative advantage optimization for stability and efficiency.

```
import torch
import numpy as np

# Hyperparameters
MAX_EPISODES = 10000
K = 8
LEARNING_RATE = 3e-4
KL_COEFF = 0.1
EPS = 0.2

# Initialize policy networks
policy_net = GraphPolicyNetwork()
old_policy_net = GraphPolicyNetwork()
```

```
old_policy_net.load_state_dict(policy_net.state_dict())
optimizer = torch.optim.Adam(policy_net.parameters(), lr=LEARNING_RATE)

# Main training loop
for episode in range(MAX_EPISODES):
    global_state = env.get_state()
    topology_list = []
    action_list = []
    reward_list = []

    # Sample K topologies and actions
    for k in range(K):
        topology = policy_net.sample_topology(global_state)
        action = policy_net.sample_action(global_state, topology, hard_mask)
        reward = env.step(action, topology)
        topology_list.append(topology)
        action_list.append(action)
        reward_list.append(reward)

    # Compute relative advantages
    r_mean = np.mean(reward_list)
    r_std = np.std(reward_list) + 1e-8
    adv = [(r - r_mean) / r_std for r in reward_list]

    # Compute loss
    loss_total = 0
    for k in range(K):
        ratio = policy_net.prob(...) / old_policy_net.prob(...)
        clip_loss = torch.min(ratio * adv[k], torch.clamp(ratio, 1-EPS, 1+EPS) * adv[k])
        kl_loss = policy_net.kl_divergence(old_policy_net, global_state)
        loss_total += -torch.mean(clip_loss) + KL_COEFF * kl_loss

    # Update
    optimizer.zero_grad()
    loss_total.backward()
    optimizer.step()
    old_policy_net.load_state_dict(policy_net.state_dict())
```

Listing 1. Topology-GRPO Core Algorithm

IV. Reward Function Design

A multi-objective weighted reward balances global goals and constraints.

Total reward:

$$R_{\text{total}} = \omega_1 R_{\text{on-time}} + \omega_2 R_{\text{cost}} + \omega_3 R_{\text{crew}} + \omega_4 R_{\text{recovery}} - R_{\text{penalty}}$$

Sub-rewards:

- On-time: $R_{\text{on-time}} = \frac{N_{\text{on-time}}}{N_{\text{total}}}$
- Cost: $R_{\text{cost}} = 1 - \frac{C_{\text{actual}}}{C_{\text{base}}}$
- Crew compliance: $R_{\text{crew}} = \frac{N_{\text{crew-compliance}}}{N_{\text{crew-total}}}$
- Recovery: $R_{\text{recovery}} = 1 - \frac{T_{\text{delay}}}{T_{\text{max-delay}}}$

Penalties are applied for regulation violations.

V. System Implementation & Deployment

A. Tech Stack

Python 3.8+, PyTorch 1.10+, NumPy, Pandas. Deployed via Kubernetes + Docker.

B. Optimization

Distributed training with Horovod, online incremental learning, replay buffer.

C. Safety & Compliance

Full decision audit trail, anomaly detection, compliance verification.

VI. Expected Performance

- Scheduling success rate: 99.5%
- Response time: 2s per decision
- On-time rate improvement: 8%
- Crew compliance: 99.9%
- System availability: 99.99%
- Support: 5000 daily flights, 500 aircraft

VII. Implementation Roadmap

1. Prototype Validation (1–3 months): Core algorithm, simulation.
2. System Integration (4–6 months): Interface with legacy systems, compliance test.
3. Full Deployment (7–12 months): Scale to entire airline, continuous optimization.

VIII. Conclusion

The MA-HRL + Topology-GRPO solution provides a scalable, efficient, and compliant framework for airline integrated scheduling. It adaptively coordinates multiple agents under dynamic constraints and achieves strong operational improvements.