Improving the Efficiency and Efficacy of Multi-Agent Reinforcement Learning on Complex Railway Networks with a Local-Critic Approach

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Abstract

The complex railway network is a challenging real-world multi-agent system usually involving thousands of agents. Current planning methods heavily depend on expert knowledge to formulate solutions for specific cases and are therefore hardly generalized to new scenarios, on which multi-agent reinforcement learning (MARL) draws significant attention. Despite some successful applications in multi-agent decision-making tasks, MARL is hard to scale to a large number of agents. This paper rethinks the curse of agents in the centralized-training-decentralized-execution (CTDE) paradigm and proposes a local-critic approach to address the issue. By combining the local critic with the PPO algorithm, we design a deep MARL algorithm denoted as local-critic PPO (LCPPO). In experiments, we evaluate the effectiveness of LCPPO on a complex railway network benchmark, Flatland, with various numbers of agents. Noticeably, LCPPO shows prominent generalizability and robustness under the changes of environments.

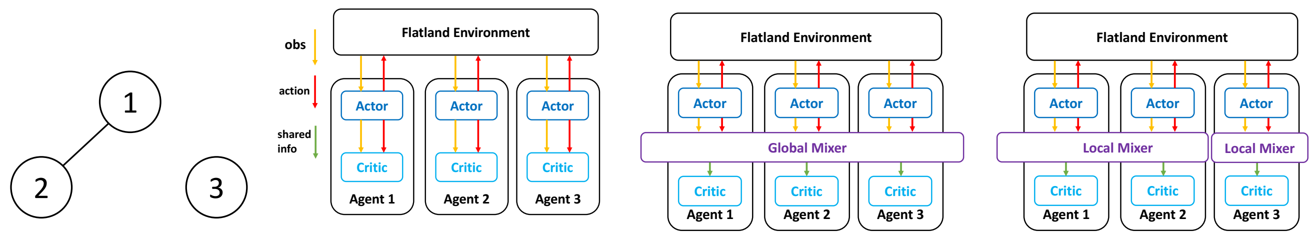
Introduction

Multi-agent reinforcement learning (MARL) has drawn significant attention in multi-agent decision-making tasks, e.g. continuous control on robots (Yan et al. 2023), playing strategic video games (Rashid et al. 2018) and distributed voltage control in power grids (Wang et al. 2022a). Although MARL has attracted significant interest in the community, its successful applications are primarily concentrated in cases where the number of agents is limited (less than 10). Most existing MARL algorithms still suffer from increasing complexity as the number of agents increases in a system. This can partially explain why MARL is hard to handle complex railway networks, where there exist up to thousands of agents. Flatland (Mohanty et al. 2020) is an open-source platform, simulating traffic on complex railway networks. In this platform, MARL has not yet outperformed the traditional optimization approaches, which naturally gives rise to a research question that *if there exists an efficient paradigm facilitating MARL to address this real-world problem*.

In this paper, we begin by investigating the underlying challenge of why existing MARL algorithms would fail on complex railway networks, then we address this challenge by proposing an efficient paradigm in critic representation. The training of the multi-agent systems is a non-stationary Markov decision process from the single agent's perspective so that independent learning (Claus and Boutilier 1998) will receive an unstable training process. To address this issue, MARL algorithms heavily rely on the centralized-training-decentralized-execution (CTDE) (Oliehoek, Spaan, and Vlassis 2008) paradigm. Based on CTDE, each agent gathers information from other agents during training (e.g., either coordinating or communicating with other agents). This information is encoded in the representation of agents' policies, so that they can still perform harmoniously with local observations during execution. Figure 1 provides an illustrative example of the distinction between independent learning and CTDE for actor-critic-based methods.

Figure 1b visualizes the independent learning that each agent has an independent critic with its own observation and action as inputs, denoted "independent critic". Figure 1c concludes most popular CTDE-based methods (Lowe et al. 2017; Wang et al. 2020a; Sunehag et al. 2018) in the MARL community. There exists a global mixer gathering all other agents' actions and observations. The global information is then fed into the critic network (denoted "global critic") to produce a more consistent value prediction and eliminate the non-stationarity. Nevertheless, the complexity of the global critic in representation grows with the number of existing agents, which causes the redundant global information and therefore the unstable learning procedure in practice (Yu et al. 2022). Furthermore, both paradigms of forming critics have not yet utilized the physical information existing in the physical system, such as the group structure 1a from the railway networks. In this work, we propose an efficient local critic (Figure 1d) paradigm, taking advantage of the observed group structure elicited from the spatial relationship among agents to mitigate the issues by the global critic mentioned above.

Nevertheless, there exist two challenges of directly applying the local critic to MARL. First, a group structure (e.g. members, connections, size) is non-stationary and each agent may be involved in different groups throughout the whole process, which prompts the introduction of a novel mixing network to deal with variations of a group structure. The output of this mixing network is usually interpreted as



(a) Group Structure (b) Independent Critic (c) Global Critic (d) Local Critic

Figure 1: Different critic architectures are shown in subfigures from (b) to (d), representing a group structure in a multi-agent system as shown in (a). (b) and (c) demonstrate two prevalent critic architectures proposed by previous works, whereas (d) demonstrates the critic architecture proposed in this paper.

the group's long-term rewards in previous works (Sunehag et al. 2018; Rashid et al. 2018), which is difficult to track in this scenario where the group is formalized and unravelled across time. The second challenge is how to appropriately clarify the contribution of each agent to a certain group. When an agent joins different groups across time, it would be non-trivial and intricate to define the past groups (or group members) its long-term rewards might reflect, which could directly influence the policy optimization.

Our main contribution is addressing the practical issues of incorporating the local critic into multi-agent systems, namely dynamic group and agent coordination. Our method is easy to incorporate into actor-critic frameworks like PPO, leading to a practical MARL algorithm, referred to as LCPPO. Furthermore, our approach demonstrates superior performance over other MARL baselines on a complex railway network simulator called Flatland, with various numbers of agents. Finally, our method shows additional generalizability and robustness with respect to environmental changes in the railway network system, which supports that LCPPO could be a promising approach to tackling real-world applications.

Related Work

The vehicle planning problem as modelled in the Flatland Environment has been an active research area within the operations research (OR) community dating back decades (Bodin and Golden 1981). To the Flatland challenge, the winning solution in 2020 (Laurent et al. 2021) was from the perspective of multi-agent path finding (MAPF) (Stern et al. 2019) combining it with other optimization techniques. For example, to handle malfunctions, an improved version of minimum communication policies (MCP) (Ma, Kumar, and Koenig 2016) was used to avoid the deadlocks by stopping some trains to maintain the order that each train visits each location. Overall, although OR methods are quite effective in known deterministic environments, they depend on expert knowledge to formulate solutions for specific cases and are therefore hardly generalized to new scenarios and stochastic setups. This motivates us to study MARL for this planning problem, which can autonomously cope with unexpected situations.

Prior works (Jiang et al. 2022) have achieved decent performances on the Flatland challenge with MARL. However, they utilize the global state for planning, which still faces the scalability issue as OR methods. One common approach to ease this issue is the centralized-training-decentralized-execution (CTDE) framework. To maintain efficiency and handle coordination concurrently, it adopts a local actor during planning and a global critic during training to gather all agents' information (Lowe et al. 2017) or decompose a global critic into individual value functions (Sunehag et al. 2018; Rashid et al. 2018; Wang et al. 2020b). They suffer from large joint state-action space and slow convergence rates during training. This directly motivates the local critic approach proposed in this paper. Yang et al. (2018) have already investigated issues of large scalability in MARL, which unfortunately simplifies agents based on static neighbouring information and is difficult to apply on dynamic railway network setups. The sub-team structure (Phan et al. 2021) is similar to our work. Their setup is still aiming to fit the global reward, which is less direct than the local group reward in our paper.

Background

Multi-Agent Reinforcement Learning

Multi-agent reinforcement learning (MARL) is a research field that combines multi-agent learning and reinforcement learning to solve a multi-agent system (MAS) described as a game-theoretical model. In this work, we apply MARL as a basic learning framework to solve complex railway networks. Following the common setting in MARL, we model the MAS as a partially observable stochastic game (POSG), which can be expressed as the following 7-tuple (Kumar and Zilberstein 2009) such that $\langle \mathcal{N}, \mathcal{S}, \mathcal{A}, \mathcal{O}, \{r_i\}_{i\in\mathcal{N}}, T, b_0 \rangle$. More specifically, $\mathcal{N} = \{1, 2, ...\}$ is a set of agents in the MAS. $\mathcal{S}$ is a set of available states. $\mathcal{O} = \times_{i\in\mathcal{N}} \mathcal{O}_i$ is a joint observation set, where $\mathcal{O}_i$ is agent i's observation set; while $\mathcal{A} = \times_{i\in\mathcal{N}} \mathcal{A}_i$ is a joint action set, where $\mathcal{A}_i$ is agent i's action set. Each agent i is equipped with a reward function to evaluate its performance such that $r_i : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$. Additionally, the transition function of the MAS can be described as follows: $T : \mathcal{S} \times \mathcal{A} \to \Delta(\mathcal{S} \times \mathcal{O})$, where $\Delta(\mathcal{X})$ is the set of all probability distributions defined over a set $\mathcal{X}$. $b_0 \in \Delta(\mathcal{S})$ is the initial state distribution. The objective of

POSG is to maximize each agent's individual discounted cumulative rewards by a stationary policy $\pi_i : \mathcal{O}_i \to \mathcal{A}_i$ such that $\max_{\pi_i} \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t r_i(s_t, a_t)]$, where $\gamma \in (0, 1)$ is a discount factor, $s_t \in \mathcal{S}$ and $a_t \in \mathcal{A}$. In MARL, the usual learning paradigm to solve POSG is called the multi-agent actor-critic framework, for which each agent individually applies the actor-critic framework to optimize its policy. Two of the most popular algorithms based on this paradigm are IPPO (de Witt et al. 2020) and MAPPO (Yu et al. 2022), which extends the vanilla multi-agent actor-critic framework by incorporating the PPO algorithm (Schulman et al. 2017). In this paper, we propose Local Critic PPO based on MAPPO via formalizing the critic with GNNs to capture sufficient information from the complex railway network.

Centralized Training Decentralized Execution

MARL algorithms are applied either as fully centralized methods where a single policy with joint action is learned for all agents or in an independent agent learning setting - also called decentralized learning where agents are optimised separately. Nevertheless, the fully centralized method could lead to the curse of dimensionality to impede learning the optimal joint policy, while the independent learning (e.g. IPPO) may result in the non-stationary learning procedure (Hernandez-Leal, Kartal, and Taylor 2019). To trade off the benefits and drawbacks of these two paradigms, centralized-training-decentralized-execution (CTDE) (Oliehoek, Spaan, and Vlassis 2008) (e.g. MAPPO) was proposed to form each agent's critic by all other agents' information (e.g. observations and actions), still maintaining the decentralized policies to approximate the joint policy as used in independent learning paradigm to avoid the curse of dimensionality. Through the lens of application, a limitation of CTDE is that it always collects the information of all agents to form a critic for an agent i, however, in physical scenarios some agents are not influential to agent i. This would inevitably cause some unnecessary fluctuations on the approximate critic, leading to potential learning instability (Yu et al. 2022). To mitigate this issue, we propose the local critic to aggregate the *sufficient* agents' information, based on the existing physical information (e.g. a tree structure describing the spatial relationship among agents), provided by the complex railway network. This would effectively filter out the information from irrelevant agents, to reduce the instability induced from the scenarios with a large number of agents. The performance of the proposed local critic sheds light on the necessity of incorporating known physical information into design when dealing with real-world problems.

Local Critic Multi-agent Reinforcement Learning (LCMARL)

As shown in background, MAPPO relies on a global critic during training, which fails to scale on complex railway networks like Flatland, with more than 10 agents. In this section, we propose an effective approach, formalizing a local group and constructing a local critic building on the local group for training. Incorporating the local critic into the popular RL algorithm PPO (Schulman et al. 2017), we achieve a practical MARL algorithm applicable to the large-scale railway planning problems, referred to as **l**ocal-**c**ritic **PPO** (LCPPO).

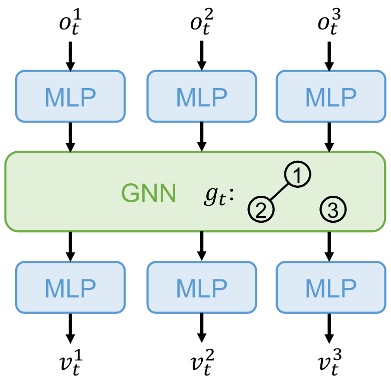
Overview

Figure 2 gives an overview of how to incorporate the local critic into the MARL framework in an actor-critic-styled algorithm, including the local-critic network and its update. Suppose N agents in a system, and they receive their local observations $\boldsymbol{o_t} = (o_t^1, o_t^2, \ldots, o_t^N)$ at each step t. Without the loss of generality, we assume global state $s_t = \boldsymbol{o_t}$. However, from the single agent's view, the system is still partially observable. The group structure g_t is a graph representation with N nodes and E edges, which can be naturally constructed in a railway system. More specifically, two agents share an edge if they are on rails connected by less than one crossroad. This setup aims to use as little information as possible, while more complex construction methods are possible. For each agent i, the number of its neighbouring agents $\mathcal{N}_t(i)$ is usually extremely less than N due to the *sparsity property* in railway systems.

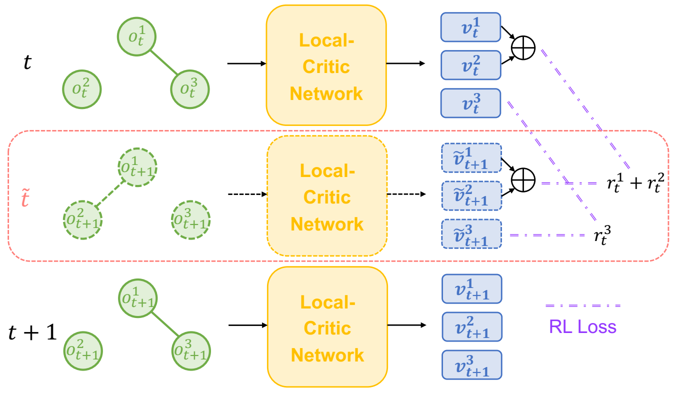
All observations are further passed into the local-critic network $V(\boldsymbol{o_t}, g_t; \phi) : \mathcal{O} \times \mathcal{G} \to \mathbb{R}$ to predict agents' individual values $\boldsymbol{v_t} = (v_t^1, v_t^2, \ldots, v_t^N)$, where $\mathcal{G}$ is the set of group structures. The local-critic network is represented as a neural network parameterized with ϕ, as illustrated in Figure 2a. The network first encodes each observation o_t^i to a hidden unit z_t^i with a multilayer perceptron (MLP) layer $z_t^i = \text{MLP}(o_t^i)$. Then the network utilizes the group structure g_t within the graph neural network (GNN) (Scarselli et al. 2009) layer to achieve the local information $h_t^i = \text{GNN}(\boldsymbol{z_t}, g_t) = \sigma(z_t^i, \bigoplus_{j \in \mathcal{N}_t(i)} \psi(z_t^i, z_t^j))$, where σ, ψ are learnable functions and $\bigoplus$ is aggregation operator. The local information h_t^i is further fed to predict the value v_t^i with an MLP layer. For each agent i, the GNN ensures its local information can only flow inside its neighbouring agents $\mathcal{N}_t(i)$ defined by the group structure g_t. If the number of neighbouring is limited to N_G and the number of agents N, the complexity of GNN is $\mathcal{O}(N_G N)$ far more efficient compared with $\mathcal{O}(N^2)$ of the global critic in Figure 1c. In practice, the GNN structure is implemented in the Transformer (Vaswani et al. 2017) architecture with the mask mechanism.

Dynamic Group

The biggest challenge in learning the local-critic network is the evolving group structure g_t. For agent i, it is urgent to discover its influence on its neighbouring agents $\mathcal{N}_t(i)$ in several successive steps, but $\mathcal{N}_t(i)$ can change at every step. To mitigate this issue, we propose a concept called the *imaginary step* $\tilde{t}$ (red dashed frame in Figure 2b). The imaginary step $\tilde{t}$ utilizes the observations $\boldsymbol{o_{t+1}}$ but maintains the group structure g_t. By passing through the local-critic network, we obtain virtual values $\boldsymbol{\tilde{v}_{t+1}} = V(\boldsymbol{o_{t+1}}, g_t)$. Since values $\boldsymbol{\tilde{v}_{t+1}}$ and values $\boldsymbol{v_t}$ (individual values at step t) are calculated with the same group structure g_t, there exists a recursive relationship (Bellman equation) with these values



(a) Local-Critic Network



(b) Local-Critic Update

Figure 2: An overview of Local-Critic Multi-agent reinforcement learning (LCMARL). The left figure represents the structure of the local-critic network with the GNN structure. The right figure describes how to update this network in MARL with a virtual imaginary step and value function loss in RL.

and rewards $\boldsymbol{r_t}$, which will be further introduced.

With the introduction of the imaginary step, values at different steps are connected with the same group structure. In details, assume the predicted values at step t are denoted as $\boldsymbol{v_t} = V(\boldsymbol{o_t}, g_t; \phi)$ for all agents, while the imaginary values at step $t+1$ are denoted as $\boldsymbol{\tilde{v}_{t+1}} = V(\boldsymbol{o_{t+1}}, g_t; \phi)$. These two values indicate the same meaning: the discounted expected cumulative return that agents can achieve under the static group structure g_t. We denote the i-th output of $V(\boldsymbol{o_t}, g_t; \phi)$ as $V_i(\boldsymbol{o_t}, g_t; \phi)$ for simplicity. According to the dynamic programming techniques (Sutton and Barto 2018), the extended Bellman equation for any i on value function V_i can be derived:

$$V_i(\boldsymbol{o_t}, g_t; \phi) = \mathbb{E}_{\boldsymbol{a_t}, \boldsymbol{r_t}, \boldsymbol{o_{t+1}}} \left[r_t^i + \gamma (V_i(\boldsymbol{o_{t+1}}, g_t; \phi) \right], \quad (1)$$

where γ is the discount factor to account for future steps. The expectation is concerning the next observations, actions and rewards. The complicated expectation computation is usually approximated by sample-based methods (Sutton and Barto 2018).

Agent Coordination

Equation 1 indicates that the value of agent i is only related to the received individual reward r_t^i. It is imperfect since agents could reach a local sub-optimal solution. Instead, we would like to encourage agents to find solutions better for global interest.

Value decomposition networks (VDN) (Sunehag et al. 2018) utilized the monotonicity of the addition calculation and summed all individual values V_i as the global value, to encourage cooperative behaviours among agents. Inspired by it, we sum all individual values inside each agent i's neighbourhood to encourage agent coordination inside this local group, which requires much less computation compared with VDN which relies on a global group. Moreover, with the evolution of the local group, agents would have a chance to coordinate with different agents. The modified Bellman equation takes place on the local-group level instead of on the single-agent level, shown as follows:

$$\sum_{j \in \mathcal{N}_t(i)} V_j(\boldsymbol{o_t}, g_t; \phi) = \mathbb{E}_{\boldsymbol{a_t}, \boldsymbol{r_t}, \boldsymbol{o_{t+1}}} \Big[\sum_{j \in \mathcal{N}_t(i)} r_t^j + \gamma \sum_{j \in \mathcal{N}_t(i)} V_j(\boldsymbol{o_{t+1}}, g_t; \phi) \Big]. \quad (2)$$

Intuitively, agent j's individual value V_j positively contributes to the local group value, thus encouraging coordination behaviours.

Practical Algorithm: LCPPO

Equation 2 describes the recursive relationship (Bellman equation) of the value function with a local-critic perspective, which takes the core position to design the loss function of value functions in actor-critic algorithms. Based on the learned value function, a better policy can be achieved by gradient-based methods. In this paper, we rely on the successful single-agent RL algorithm PPO (Schulman et al. 2017) as the backbone, and develop a novel MARL algorithm, referred to as **L**ocal-**C**ritic **PPO** (**LCPPO**). The specific procedure is shown in Algorithm 1. Agents are assumed as homogeneous. The policy function is denoted as $\pi_i(o_t^i; \theta) = \pi(o_t^i; \theta)$ for any agent i, with parameters θ, whereas the value function is denoted as $V(\boldsymbol{o_t}, g_t; \phi)$, with parameters ϕ. Agent i's individual value function is denoted as $V_i(\boldsymbol{o_t}, g_t; \phi)$, which is the i-th output of $V(\boldsymbol{o_t}, g; \phi)$. LCPPO can be extended to heterogeneous agents with individual policy and value functions but left to future work. For each agent i's neighbouring group $\mathcal{N}_t(i)$ derived from group structure g_t, the group value is defined as the sum of group members' individual values: $v_t^{\mathcal{N}_t(i)} = \sum_{m \in \mathcal{N}_t(i)} V_m(\boldsymbol{o_t}, g_t; \phi)$. The key modification to PPO method is on Line 9 that the local group reward $r_t^{\mathcal{N}_t(i)}$ is modified with an additional correction term $\gamma(\tilde{v}_{t+1}^{\mathcal{N}_t(i)} - v_{t+1}^{\mathcal{N}_{t+1}(i)})$. This term is designed to compensate

Algorithm 1: LCPPO

```
Input: initial parameters $\theta_0$ for policy function $\pi$, initial parameters $\phi_0$ for value function $V$
for $k = 0, 1, 2, \cdots, K$ do
    Set data buffer $\mathcal{D}_k = \emptyset$
    for $j = 0, 1, 2, \cdots, J$ do
        Collect trajectory $\tau_j = \{\boldsymbol{o_0}, \boldsymbol{a_0}, \boldsymbol{r_0}, g_0, \boldsymbol{o_1}, \cdots\}$ by executing actions $\boldsymbol{a_t} \sim \pi(\boldsymbol{a_t}|\boldsymbol{o_t};\theta) = \prod_{i=1}^{N} \pi(a_t^i|o_t^i;\theta)$ in the environment at each step $t$
        for each step $t$ and each agent $i$'s neighbouring group $\mathcal{N}_t(i)$ derived from $g_t$ do
            Compute values $v_t^{\mathcal{N}_t(i)} = \sum_{m\in\mathcal{N}_t(i)} V_m(\boldsymbol{o_t}, g_t; \phi)$
            Compute virtual values $\tilde{v}_{t+1}^{\mathcal{N}_t(i)} = \sum_{m\in\mathcal{N}_t(i)} V_m(\boldsymbol{o_{t+1}}, g_t; \phi)$
            Compute local group reward $r_t^{\mathcal{N}_t(i)} = \sum_{m\in\mathcal{N}_t(i)} r_t^m + \gamma(\tilde{v}_{t+1}^{\mathcal{N}_t(i)} - v_{t+1}^{\mathcal{N}_{t+1}(i)})$
            Compute advantage estimates $\hat{A}_t^{\mathcal{N}_t(i)}$ via GAE (Schulman et al. 2017) with local group reward $r_t^{\mathcal{N}_t(i)}$ and value $v_t^{\mathcal{N}_t(i)}$
            Compute rewards-to-go $\hat{R}_t^{\mathcal{N}_t(i)} = \hat{A}_t^{\mathcal{N}_t(i)} + v_t^{\mathcal{N}_t(i)}$
            $\tau_j \leftarrow \tau_j \cup \{v_t^{\mathcal{N}_t(i)}, \hat{A}_t^{\mathcal{N}_t(i)}, \hat{R}_t^{\mathcal{N}_t(i)}\}$
        end for
        $\mathcal{D}_k \leftarrow \mathcal{D}_k \cup \{\tau_j\}$
    end for
    Update value function's parameters $\phi$ with Adam optimizer (Kingma and Ba 2015) by fitting rewards-to-go:
        $\phi_{k+1} = \arg\min_{\phi} \sum_{\tau\in\mathcal{D}_k} \sum_{t=0} \sum_{i\in\mathcal{N}} \Big( \sum_{m\in\mathcal{N}_t(i)} V_m(\boldsymbol{o_t}, g_t; \phi) - \hat{R}_t^{\mathcal{N}_t(i)} \Big)^2$
    Update policy function's parameters $\theta$ with Adam optimizer by maximizing multi-agent PPO objective:
        $\theta_{k+1} = \arg\max_{\theta} \sum_{\tau\in\mathcal{D}_k} \sum_{t=0} \sum_{i\in\mathcal{N}} \sum_{m\in\mathcal{N}_t(i)} \min\big(c_t^m(\theta)\hat{A}_t^{\mathcal{N}_t(i)}, \textbf{clip}(c_t^m(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t^{\mathcal{N}_t(i)}\big)$, where $c_t^m(\theta) = \frac{\pi(a_t^m|o_t^m;\theta)}{\pi(a_t^m|o_t^m;\theta_k)}$
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the calculations on advantages $\hat{A}_t^{\mathcal{N}_t(i)}$, so that it stands for the virtual values instead of the real values, following Equation 2.

Experiments

Experimental Setup

Task Description We evaluate the LCPPO on Flatland (Mohanty et al. 2020), a simplified grid environment to simulate the railway networks with an easy-to-use machine learning interface. The goal is to control each vehicle with different routes to arrive safely and punctually. Figure 4 visualizes the running process in Flatland. We mainly follow the official environmental configurations[1] with 10/20/30 agents respectively. In particular, the map size is 30×30 with 3 cities (2 cities for 10 agents). The max rails between cities are 2 and there are 2 rail pairs in each city. The malfunction rate is 0 and the speed for the vehicle is 1.0 grid per step and varied in later analysis.

Regarding the MARL setup, we follow the previous setup (Jiang et al. 2022) that each agent i receives a local observation o_t^i at step t consisting of two parts: agent attributes X^{attr} and tree-structured representation X^{tree}. X^{attr} describes the individual attributes of each agent with 83 dimensions, e.g. scheduled departure and arrival time. X^{tree} represents the spatial information on the grid environment, which is encoded as the tree structure $X^{\text{tree}} = (\text{node}_{v=1}^{V}, \text{edge}_{e=1}^{E})$ includes $V = 31$ nodes with 13-dimensional node attributes node_v and $E = 30$ edges with 4-dimensional attributes edge_e indicating connected nodes, concatenated to a 606-dimensional vector. All the information is derived from the spanning tree, which is constructed by traversing from the agent's location and branch at each possible crossroad. Please refer to Jiang et al. (2022) for the detailed description of the spanning tree and attributes. The action space includes five discrete actions: do nothing, go forward, stop, turn left, and turn right. Regarding the group structure needed by LCPPO during training, it's defined as follows: for each agent, any other agents who appear in the first level of its spanning tree belong to the same group. The common group size is less than 3, which is much less than the total number and guarantees the efficiency of LCPPO.

Evaluation Metric We adopt multiple objectives to evaluate the performance of different methods. Each agent receives an individual reward signal at each step, consisting of the following items:

- **Arrival Reward:** $r_t^a = 1$ if the agent primarily reaches the target and $r_t^a = 0$ otherwise;
- **Deadlock Penalty:** $r_t^l = -1$ if the agent primarily immerses in a deadlock and $r_t^l = 0$ otherwise. A deadlock happens when two trains step into a single trail from opposite directions. The deadlock quickly blocks the rails and catastrophically paralyzes the whole system, and thus should be penalized.
- **Environment Reward:** To encourage the train to arrive on time, Flatland environment (Mohanty et al. 2020) provides an environmental reward defined as

$$r_t^e = \begin{cases} 1.0, & \text{if } t \le B \text{ AND new arrival} \\ (B-t)/T_{\max} + 1, & \text{if } B < t < T_{\max} \text{ AND new arrival} \\ (B-d)/T_{\max}, & \text{if } t = T_{\max} \text{ AND not arrival} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

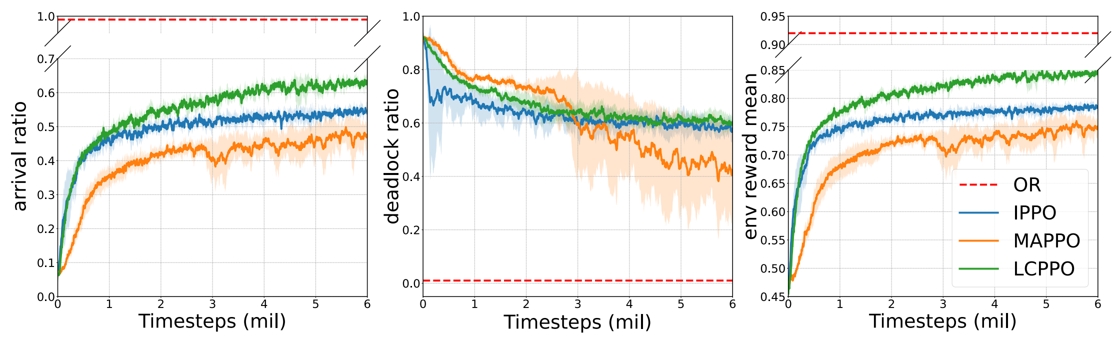
  where B is the latest arrival time, $T_{\max}$ is the system's maximum running steps and d is the shortest path Manhattan distance between the train's position and target at $T_{\max}$. The intuition of the reward is to punish the delays after the scheduled latest time.

The final reward for agent i is the weighted sum of all terms above: $r_t^i = c_e r_t^e + c_a r_t^a + c_l r_t^l$, where $c_e = 1.0$, $c_a = 5.0$ and $c_l = 2.5$ follows previous work (Jiang et al. 2022).

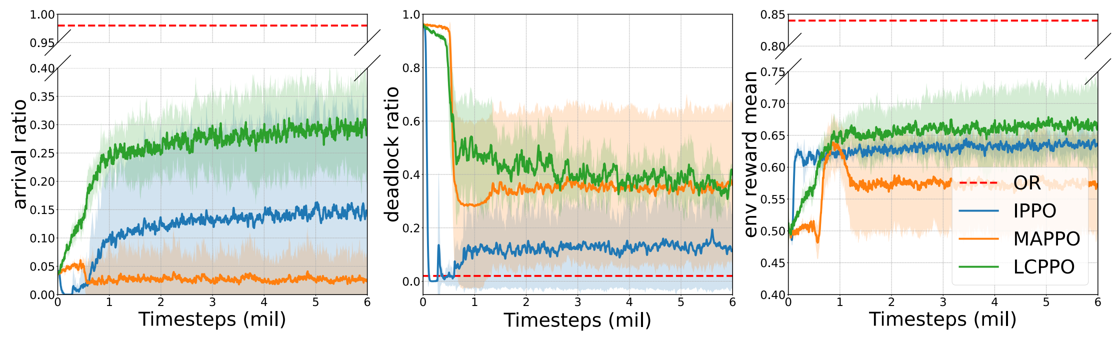
Baselines and Implementation To ensure a fair comparison, we select representative CTDE-based methods, which only use local information during execution, and one SOTA OR-based method with global optimization.

- **IPPO** implements the structure as in Figure 1b. Each critic only relies on local observation during training.
- **MAPPO** represents the structure as in Figure 1c and previous work (Yu et al. 2022). The critic network gathers all

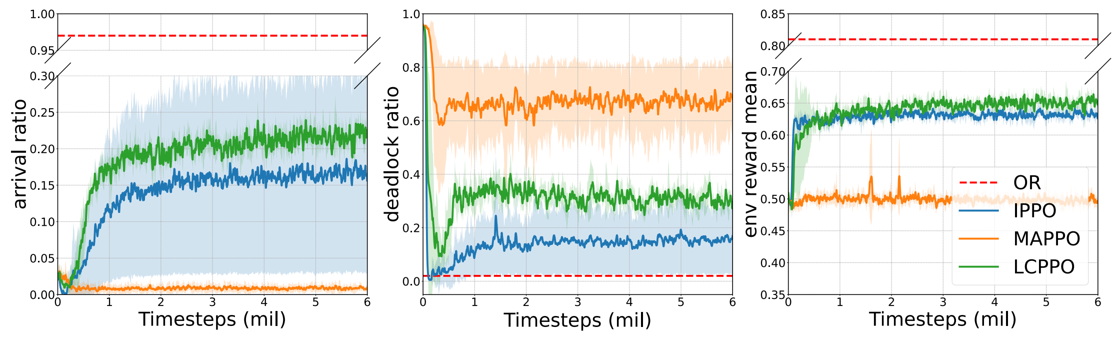
[1]flatland.aicrowd.com/challenges/flatland3.html



(a) 10 Agents.



(b) 20 Agents.



(c) 30 Agents.

Figure 3: The training performances on the Flatland simulator with variant numbers of agents. All experiments are carried out with 5 random seeds and the average performances across all agents are plotted with standard deviation as shaded area.

agents' observations as input and predicts the value. Notably, the global critic fits the global reward as the sum of individual rewards for global cooperation.

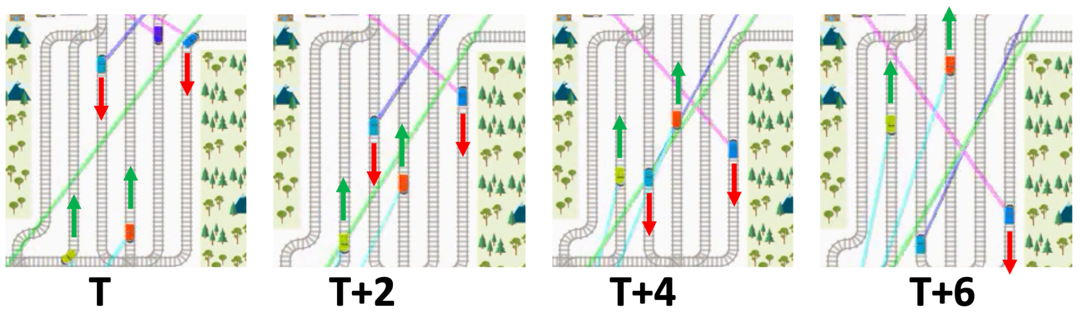
- **LCPPO** follows Algorithm 1 introduced in this paper. Theoretically, the critic network only utilizes observations from its neighbours. Practically, we use all agents' observations and adopt a Transformer (Vaswani et al. 2017) layer with the mask mechanism to imitate the effects.
- **OR** is the winning solution of the flatland challenge from the operations research field[2]. OR method utilizes global information and expert knowledge of the environment to execute a thorough planning process at the beginning of the episode. Although this setup is different from RL-based methods, it is included to indicate the current performance gap left for RL-based methods.

All MARL baselines share the same actor network structure of a 2-layer feedforward neural network with 128 and 64 hidden units each. The critic network has a hidden-layer structure as the actor network, and there is an additional transformer layer with 128 hidden units and 4 heads to group local information in LCPPO. Other hyperparameters are demonstrated in the supplementary material. The parameter sharing technique (de Witt et al. 2020) is enabled among agents for efficient learning.

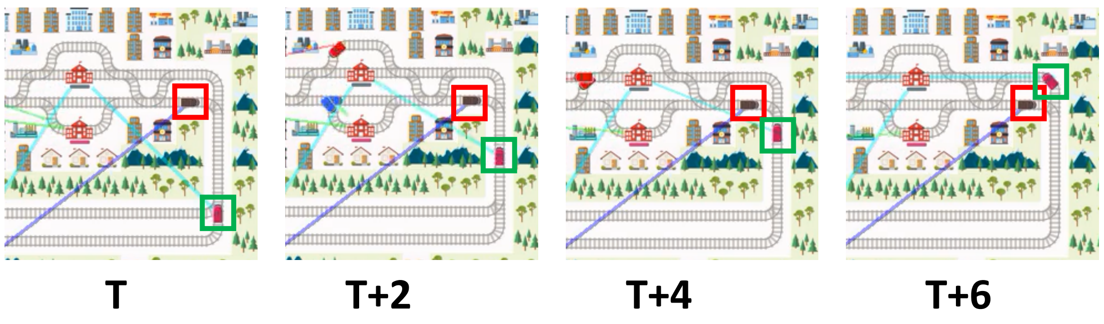
Main Results

The main results of 10/20/30 agents are shown in Figure 3. All experiments are carried out with 5 random seeds and the

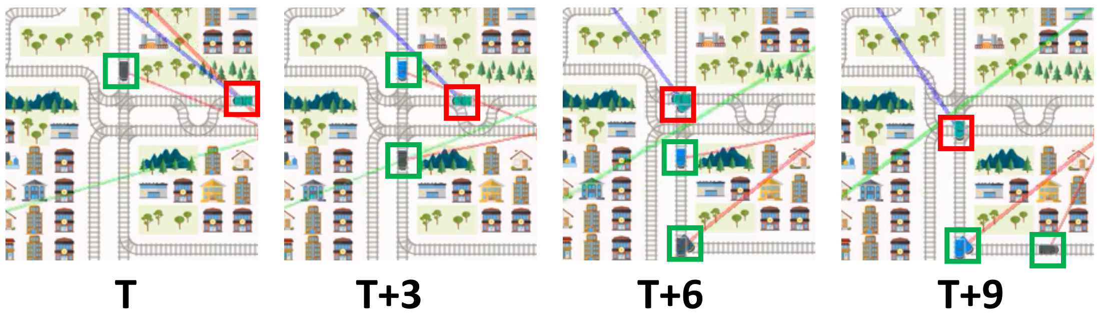
[2]github.com/Jiaoyang-Li/Flatland



(a) Passing Different trails in different directions.



(b) Waiting for closed-target agents passing.



(c) Waiting for same-direction group agents passing.

Figure 4: Visualization of agents' policies learned by LCPPO algorithm.

average performances are plotted with standard deviation as shaded area. All evaluation metrics are averaged across participating agents. In terms of the arrival ratio and environmental reward, all experiments share a similar trend of LCPPO $>$ IPPO $>$ MAPPO, which is strong evidence that the local critic successfully guides the coordination of agents thus leading to more on-time arrivals. Notably, MAPPO can't learn meaningful behaviours with the increasing number of agents. This result complies with the curse of agent issues occurring in the MARL area as explained in the introduction. Regarding the deadlock ratio, LCPPO is usually slightly larger than IPPO, which is considered acceptable when more agents depart and crowd the network. We hope future work could analyze how to better coordinate these two objectives. Beyond that, we visualize the agents' policies learned by LCPPO in Figure 4 to further explain the behaviours. In general, we believe that LCPPO masters 2 skills to outperform other baselines: (i) Different trails allow trains to pass in different directions as in Figure 4a, which not only avoids deadlock but also regulates the traffic; (ii) Trains learn to wait for other trains to pass first for group benefit. The red-box agent waits for another agent to reach targets first in Figure 4b and stops for other same-direction agents to pass in Figure 4c.

Besides, the OR method consistently outperforms LCPPO in terms of all metrics, especially for the almost perfect deadlock ratio and arrival ratio, showing the current performance gap for RL-based methods. We record the average time cost of OR and LCPPO in Table 1. Notably, the time cost for OR is calculated as the sum of the initial plan and interval replans, while the time cost for LCPPO is calculated as the episode inference time (this value should be compa-

Algorithms	Number of Agents		
	10 Agents	*20 Agents*	*30 Agents*
OR	75	421	862
LCPPO	75	218	269

Table 1: The average time cost of OR and LCPPO with variant numbers of agents. The unit is in milliseconds.

rable for IPPO and MAPPO as they adopt the same decentralized actor network). The time cost for LCPPO doesn't scale as much as the OR method, attributed to the CTDE framework. This shows the potential of LCPPO as a critical extension of planning methods in large-scale and stochastic railway systems in future work.

Generalization

Generalization (Kirk et al. 2023) is essential for learning-based methods since there might be mismatches between training and testing environments in practice, which also applies to the railway system. There are various malfunctions in real-world railway trails. Besides, it's common to add or reduce train routes, which all require rescheduling plans. In theory, LCPPO only utilizes local information to guide planning behaviours. When mismatches happen in the system, local groups close to the mismatches need re-planning and other groups are not influenced. Compared with the global critic method, a malfunction could influence all agents since it has not been during training.

To demonstrate the generalization of LCPPO, we design the following experimental setups: we first utilize different algorithms to train planning policies on environments defined in the setups. Later on, certain components of the environment are modified to simulate the mismatch in the system and all policies are tested on newly changed environments without further tuning. Regarding the changing components, we consider the following scenarios:

- **Malfunctions:** Trains are randomly stopped for random duration. The stopped train would block the trail and block other trains passing. This stochastic process follows the Poisson process. The mean rate of the Poisson process is 0.0001. The stopping duration ranges from 15 steps to 50 steps.
- **Speeds:** All trains have speed with one grid per step during training. During testing, 1/4 of trains maintain this speed, while 1/4 with one grid per 2 steps, 1/4 with one grid per 3 steps and 1/4 with one grid per 4 steps.
- **Agents:** There are 20 trains in the network during training. 10 more agents are added during testing to challenge the generalization ability.

All experiments are carried out with 5 random seeds and 20 episodes for each seed and we report the average arrival ratio and its standard deviation in Table 2. Apparently, LCPPO is the most robust algorithm among all MARL baselines. The global critic method (MAPPO) is the least favourite method under environmental mismatches. This proves our concerns about current state-of-the-art MARL methods. The number of agents is the most influential factor to all baselines, which calls theories from open team research (Rahman et al. 2021).

Algorithms	Test Scenarios		
	Malfunctions	*Speeds*	*Agents*
IPPO	0.16 ± 0.19	0.12 ± 0.15	0.11 ± 0.14
MAPPO	0.02 ± 0.01	0.03 ± 0.01	0.02 ± 0.01
LCPPO	0.24 ± 0.11	0.19 ± 0.10	0.18 ± 0.09

Table 2: The average arrival ratio of all baselines under different test scenarios.

Conclusion

This paper focuses on the applications of MARL on complex network railway networks. The failure of state-of-the-art MARL methods in such a large-scale environment directly motivates this work. We proposed the local critic idea and achieved an efficient MARL algorithm LCPPO. LCPPO scales efficiently with the number of agents in the Flatland environment and performs more robustly than baselines.

Despite the advantages provided by the local critic, LCPPO still renders some deadlocks and unsuccessful plannings, which is non-negligible in real-world applications. It implies that the CTDE paradigm might not be enough to handle the coordination on agents (Zhou et al. 2023). Therefore, it would be beneficial to include communications among local groups or global information (graph structure, other agents' observations...) during execution for global optimal solutions. Besides, current updates on the value function rely on the sum of rewards in the local group, which treats all agents with identical importance. This assumption might be wrong for heterogeneous multi-agent systems. A more advanced credit assignment technique should be considered (Rashid et al. 2018; Wang et al. 2022b) and extended to dynamic group scenarios.

Acknowledgments

This research receives funding from the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie grant agreement No. 953348 (ELO-X). Jianhong Wang is fully supported by UKRI Turing AI World-Leading Researcher Fellowship, EP/W002973/1.

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