

An Introduction to Multi-Agent Reinforcement Learning and Review of its Application to Autonomous Mobility

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Abstract—Many scenarios in mobility and traffic involve multiple different agents that need to cooperate to find a joint solution. Recent advances in behavioral planning use Reinforcement Learning to find effective and performant behavior strategies. However, as autonomous vehicles and vehicle-to-X communications become more mature, solutions that only utilize single, independent agents leave potential performance gains on the road. Multi-Agent Reinforcement Learning (MARL) is a research field aiming to find optimal solutions for multiple agents interacting with each other. This work gives an overview of the field to researchers in autonomous mobility. We first explain MARL and introduce important concepts. Then, we discuss the central paradigms that underlie MARL algorithms and give an overview of state-of-the-art methods and ideas in each paradigm. With this background, we survey applications of MARL in autonomous mobility scenarios and give an overview of existing scenarios and implementations.

I. INTRODUCTION

Artificial intelligence (AI) is increasingly being deployed in many applications and devices operating in a connected and cooperative environment. This is particularly relevant in autonomous mobility and traffic scenarios, like the ones shown in Fig. 1, where multiple agents need to interact to find a common solution. As cooperation and communication between the agents are important in these problems, single-agent solutions, such as reinforcement learning (RL), often fall short of expectations. Instead, multi-agent reinforcement learning (MARL) deals with multi-agent problems and aims to find policies that help multiple vehicles reach their individual and common objectives.

MARL aims at finding optimal strategies for agents in settings where multiple agents interact in the same environment. This allows a variety of new solutions that build on concepts such as cooperation [1] or competition [2]. However, multi-agent settings also introduce challenges, including potentially missing or inadequate communication, difficulties in credit assignment to agents, and environment non-stationarity. This survey highlights key principles and paradigms in MARL research and gives an overview of possible applications and challenges for MARL in autonomous mobility.

The paper is structured as follows. Basics of RL are provided in Sec. II before central concepts of MARL in Sec. III. Sec. IV summarizes state-of-the-art MARL algorithms and explains core paradigms. Sec. V gives an overview of application fields. Sec. VI concludes.

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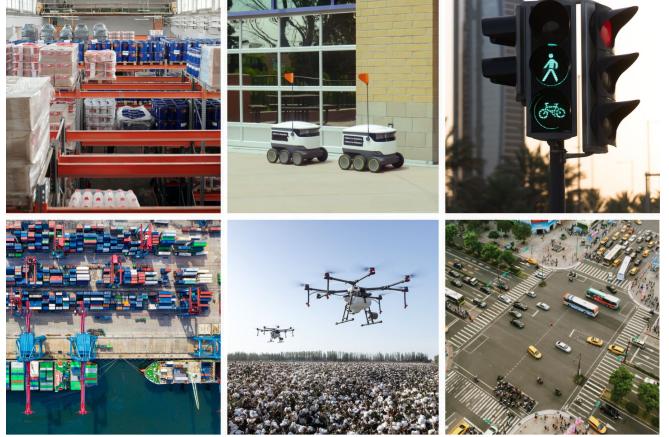


Fig. 1: MARL applications: Intelligent warehouses and logistics, drone fleets for delivery and agriculture, traffic flow control, and automated driving (image source: Pexels/Pixabay).

II. BASICS: REINFORCEMENT LEARNING

Single-agent RL is designed to solve a class of problems known as Markov decision processes (MDPs). In an MDP, a single agent interacts with an environment by taking certain actions a depending on the state s of the environment. These actions may change the state of the environment. The agent receives a reward r and aims at maximizing the expected return, i.e., the sum of rewards gained in the environment discounted by a factor γ (that weights future rewards) by finding an optimal policy π^* (i.e., the *behavior*; $*$ denotes optimality) that maps states to actions. A single step in the environment is known as a transition sample (s, a, r, s') [3].

We describe an MDP by a quin-tuple (S, A, P, R, γ) where S and A refer to state and action space, P denotes the transition probability from a state s to a successor state s' given an action a , R denotes the reward function received by the agent for the transition from (s, a) to s' , and $\gamma \in [0; 1]$ is the discount factor that trades instantaneous over future rewards.

Two major paradigms in RL are value-based and policy gradient methods. Value-based methods, such as DQN [4], estimate the utility of an action using a parametrized Q-network Q_θ ; the policy is then formed by greedily following the actions with the highest estimated values. Instead, policy gradient methods directly optimize a parametrized policy π_θ to take actions that lead to a high reward more likely. Recent work in RL, e.g., PPO [5] combines both paradigms into an actor-critic architecture that uses a value-based critic to improve updates to the actor (or policy).

III. MULTI-AGENT REINFORCEMENT LEARNING

In MARL, multiple agents are concurrently optimized to find optimal policies. Compared to the single-agent RL settings, this introduces several important differences and possibilities, which we want to highlight in this section.

1) *Observability in MARL*: In RL, observability describes whether an agent can perceive the entire environment state fully or partially. A classical MDP is defined to be fully observable: The agent directly perceives the environment state s . Partial observability is described by a partially observable Markov decision process (POMDPs) and modeled by adding a (potentially lossy) observation function converting an environment state s to an observation o . POMDPs often present more challenging, real-world applications. For applied research, some scenarios (i.e., robots inside a controlled warehouse environment with enough sensors) can be assumed to be fully observable. Most real-world mobility applications, like traffic scenarios, are partially observable.

MARL provides the opportunity to combine partial observations from multiple agents to gather more information. Several paradigms of MARL research, like communication or cooperation, explicitly or implicitly use this opportunity to improve performance. Many MARL methods use Recurrent Neural Networks (RNNs) to aggregate observations over time into more complete observations [6].

2) *Centrality*: Different MARL settings can be distinguished by how much agents can communicate with each other. In a fully decentralized problem, agents have no means of communication, while a fully centralized setting allows one central entity to perceive and control all agents. This distinction affects whether the state and action spaces for all agents are disjoint (decentralized) or joint (fully centralized). Most MARL algorithms are neither decentralized nor fully centralized; we explain different communication and interaction paradigms in Sec. IV.

3) *Heterogeneous vs. Homogeneous agents*: In general, MARL does not require all agents to be similar. Heterogeneous agents can have different observation and action spaces, like cars and traffic lights. However, in many MARL environments, the agents are homogeneous, meaning they have the same state and action space. For example, many cars require similar behavior in an autonomous driving setting. For homogeneous agents, parameter sharing can be introduced to effectively jointly learn their policies. This is advantageous as the amount of trainable parameters is reduced, allowing for shorter training times. More efficient training is enabled as the experiences of all agents are used. However, different behavior at execution time is still possible because each agent has unique observations.

4) *Cooperative vs. Competitive*: An important difference between MARL environments is how the goals of each agent relate to each other. This can be divided into fully cooperative, fully competitive, and mixed cooperative-competitive.

In cooperative settings, all agents aim to achieve a common goal. For example, all agents want to reach their destination undamaged. Usually, all agents share a common reward function [7]. This work focuses on cooperative MARL

because autonomous mobility scenarios are best characterized by shared goals (e.g., reaching each agent's destination unharmed) rather than by competitive objectives.

By contrast, competitive settings, e.g., card or board games, are usually modeled as zero-sum Markov games where the return of all agents sums to zero [8]. Mixed settings combine cooperative and competitive agents that use general-sum returns. For instance, in team games, agents have to cooperate with their teammates while competing with the opposing teams [8]. Littmann et al. [9] state that optimal play can be guaranteed against an arbitrary opponent in competitive settings, whereas strong assumptions must be made to guarantee convergence for cooperative environments.

5) *Scalability*: While simple MARL problems have a relatively small number of agents, many real-world mobility scenarios involve hundreds or thousands of individual traffic participants. Modern simulators, like SUMO [10] or CityFlow [11], can simulate entire neighborhoods or small cities and model how hundreds of traffic lights affect the traffic flow. Consequently, algorithms must scale to these large agent numbers correctly and efficiently. For example, a simple centralized entity that uses the joint observation and action space of all agents would be impossible to train. In contrast, independent agents (although less performant for a smaller number of agents) could still operate. This problem is known as scalability, and we discuss potential solutions in Sec. IV.

6) *Global vs. Local rewards*: Single-agent RL environments have a single reward definition specifying the objective for the agent. Cooperative multi-agent settings can either have a single global reward or multiple local rewards, one for each agent [12]. By contrast, global rewards only depend on the global state. They are easy to compute and specify but often lead to inefficient training because agents are never explicitly rewarded or penalized for their own actions [13]. Local rewards can reflect each agent's contribution to the cooperating group. This makes it easier to learn and improves convergence, especially in decentralized settings that do not have other explicit cooperation [14]. However, it is usually challenging to design and implement a reward function that correctly rewards individual agents for their contributions [15]. Algorithms that aim to solve the problem of credit assignment described in Sec. IV-B explicitly learn how global rewards can be disentangled into local rewards to solve this.

IV. ALGORITHMS FOR MARL

We organize algorithms for MARL into four categories based on their underlying paradigm, as illustrated in Fig. 2. We order them from independent to fully connected agents. The four paradigms described in the next paragraph are: Fully decentralized algorithms, credit assignment, communicating agents, algorithms with centralized training and decentralized execution. All algorithms surveyed in this work are summarized in Table I. In addition to paradigm and algorithm type, the table also lists available open-source implementations of these algorithms.

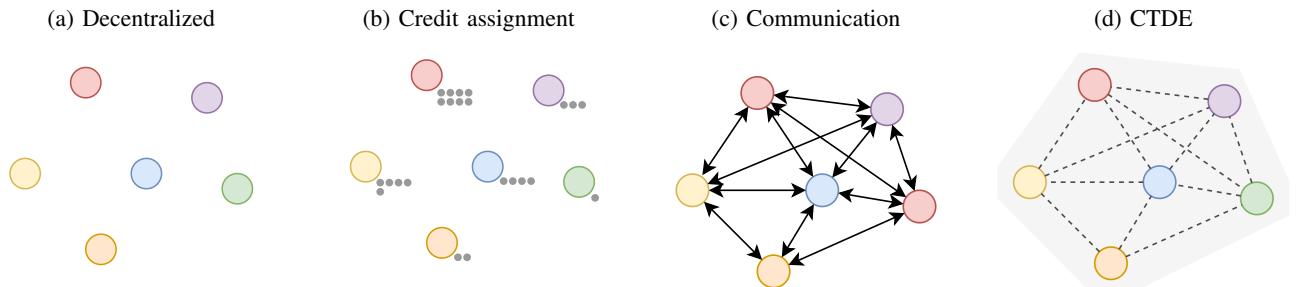


Fig. 2: Four categories of MARL approaches based on communication and cooperation: (a) In a decentralized setting, agents (colored circles) operate and learn independently; (b) Credit assignment techniques use an explicit mechanism that assigns the reward (grey circles) to individual agents; (c) Agents operate independently but have access to a communication medium to exchange messages (black arrows). (d) In Centralized training with decentralized execution (CTDE), agents use a shared critic (gray background) to improve performance during training. After training, the critic is no longer used, and agents operate independently.

Algorithm Frameworks. There are many publicly available implementations of MARL algorithms, provided both through author implementations and larger frameworks. RL-Lib [34] is an open-source reinforcement learning library that aims at providing high-performance implementations for RL algorithms. Many single-agent RL algorithms are implemented, which can be extended to the multi-agent setting. Moreover, some MARL-specific algorithms are available. EpyMARL is another framework comprising a wide range of algorithms. However, only discrete actions are available [35]. Mava is designed for scalable MARL training and execution. It allows for discrete and continuous actions [36]. MALib is specialized in scalable population-based MARL [37]. Networked MARL (NMARL) is a repository of MARL algorithms for networked system control [28]. Table II lists the implementation framework, if available, as well.

A. Decentralized: Learning independently

The fully decentralized setting assumes that agents learn entirely independently. Usually, multiple agents learn individual single-agent RL algorithms concurrently. To that end, each agent has an independent observation, policy, and algorithm - the only interaction exists through the environment. This kind of algorithm is often used as a baseline and includes independent Q-learning (IQL) [16], independent advantage actor critic (IA2C) [17] or independent proximal policy optimization (IPPO) [18]. Typically, independent agents perform worse than optimized cooperating agents in centralized settings. However, the performance benefits of more complicated approaches vary wildly between environments - in some cases, independent agents are on par with or can outperform cooperating agents [16], [18].

While it is easy to adapt single-agent RL algorithms to these settings, decentralized environments violate the stationary Markov property (i.e., the probability transitions P , which define the system dynamics, change). In particular, all other agents are considered part of the environment from an agent's perspective. Therefore, contrary to single-agent RL, convergence is not guaranteed [38]. However, decentralized algorithms do not need to deal with scalability issues which is a frequent challenge in autonomous mobility scenarios.

B. Credit assignment

Most MARL environments do not explicitly disentangle reward functions for different agents and use global rewards instead. This is problematic during training [13]. Credit assignment methods aim to convert this global reward into an estimated, per-agent local reward. For example, if vehicles are trained to move autonomously, and a vehicle causes a crash, it is desirable to only punish the perpetrator.

Credit assignment methods can be grouped into explicit and implicit credit assignment methods. Explicit methods estimate each agent's contributions against a certain baseline. COMA [19] proposes a counterfactual baseline, where the global reward is compared to the reward received if the agent's action is replaced by a default action. This approach omits correlations between the agents, leading to inefficiency in complex settings. To circumvent this problem, Li et al. [20] introduce Shapley counterfactual credit assignment that guides the training by estimating the individual credit for each agent using Shapley Values. Shapley Value is a concept from cooperative game theory quantifying the contribution of each player to the coalition [39].

Implicit credit assignment aims at learning how to decompose the shared reward function into individual value functions [40]. Sun et al. introduce a value decomposition network (VDN), which learns to decompose the shared value function into individual value functions [21]. However, it assumes additive individual functions. QMIX [22] builds on VDN and removes this limitation by decomposing the global reward into an arbitrary non-linear combination of per-agent value functions. To make the optimization tractable, QMIX only constrains this combination to be monotonous with respect to the contribution of individual agents [22].

While this monotony constraint allows a decentralized execution, Mah et al. [23] argue that it does not hold for arbitrary Q-functions and makes exploration inefficient. They introduce a hierarchical method, i.e., multi-agent variational exploration (MAVEN), that introduces a central latent space and diversifies exploration among agents [23]. However, recent work [24] argues that this exploration is still inadequate

TABLE I: We sort algorithms into the paradigms explained in Fig.2 according to their primary contribution. Some algorithms can be assigned to multiple paradigms. Additionally, we note if algorithms make use of an explicit communication mechanism between agents. The type is either value-based (V), policy-based (P), or actor-critic (AC).

Name	Year	Communication	Type	Framework
Independent Agents, Section IV-A				
IQL [16]	1993	No	V	EpyMARL ¹ , RLLib ² , MALib ⁴
IA2C [17]	2020	No	AC	EpyMARL ¹ , RLLib ² , MALib ⁴
IPPO [18]	2020	No	AC	EpyMARL ¹ , RLLib ² , MALib ⁴
Credit Assignment, Section IV-B				
COMA [19]	2018	No	AC	EpyMARL ¹
Shapley counterfactual credit assignment [20]	2021	No	Value	-/-
VDN [21]	2018	No	V	EpyMARL ¹ , Mava ³
QMIX [22]	2018	No	V	EpyMARL ¹ , RLLib ² , Mava ³ , MALib ⁴
MAVEN [23]	2019	No	Hybrid	Author's implementation ⁵
Q-DPP [24]	2020	No	V	Author's implementation ⁶
Communication, Section IV-C				
RIAL [6]	2016	Yes	V	Author's implementation ⁷
DIAL [6]	2016	Yes	V	Mava ³ , NMARL ⁸
CommNet [25]	2016	Yes	P	NMARL ⁸
ATOC [26]	2018	Yes	AC	-/-
IC3Net [27]	2019	Yes	P	Author's implementation ⁹
NeurComm [28]	2020	Yes	AC	NMARL ⁸
Mean-field MARL [29]	2018	No	V/AC	Author's implementation ¹⁰
Dec-Neural-AC [30]	2021	No	AC	-/-
Centralized Training, Decentralized Execution, Section IV-D				
MADDPG [31]	2017	No	AC	EpyMARL ¹ , RLLib ² , MALib ⁴ , Mava ³
MAPPO [32]	2021	No	AC	EpyMARL ¹ , Mava ³
Recurrent policy optimization [33]	2021	No	AC	Authors implementation ¹¹

¹ github.com/ueo-agents/epymarl

² docs.ray.io/en/master/rllib/index.html

³ github.com/instadeepai/Mava

⁴ github.com/sjtu-marl/malib

⁵ github.com/AnujMahajanOxf/MAVEN

⁶ github.com/QDPP-GitHub/QDPP

⁷ github.com/iassael/learning-to-communicate

⁸ github.com/ctsl98859/deeprl_network

⁹ github.com/IC3Net/IC3Net

¹⁰ github.com/mlii/mfrl

¹¹ github.com/kargarisaac/macrpo

and proposes a linear-time sampler that helps agents cover orthogonal directions in state space during training.

C. Learning Communication

To allow agents to cooperate, a large body of work introduces an explicit communication layer to the algorithms. This information exchange allows agents to widen their observation space and cooperate. We discuss algorithms that use explicit communication between agents.

Foerster et al. [6] proposed two approaches for learning communication between independent agents. In Reinforced Inter-Agent Learning (RIAL), each agent has an additional network to generate a communication message for the other agents. For Differentiable Inter-Agent Learning (DIAL), the gradients of the other agents are fed through the communication channel into the communication network. This allows for end-to-end training across the agents. RIAL is only trainable within an agent. In contrast to discrete connections in RIAL and DIAL, CommNet [25] learns a continuous communication channel jointly with the policy. Through this channel, the agents receive the summed transmission of the other agents. Then, the input of each hidden layer for each agent is the previous layer and the communication message.

In recent work, communication has been viewed more ambiguously. Communication introduces costs, especially as the

number of agents grows. Additionally, communication massively increases the amount of information available to each agent, making it harder to identify crucial information [26]. Recent work has thus focused on different mechanisms to decide if an agent should communicate at all.

Jiang and Lu [27] propose an attentional communication model (ATOC) that uses local information to decide if an agent should initiate communication. Agents form a dynamic group of local communicating agents that can coordinate with a shared communication medium. In a different line of work, the individualized controlled continuous communication model (IC3Net) [27] uses recurrent neural network (RNN) policies and allows agents to share the RNN's hidden state through a designated action. This is particularly useful in competitive scenarios as agents can block communication.

Another approach to restricting communication is networked MARL. Contrary to attentional communication, these networks limit the agents' communication to their local neighbors. Chu et al. [28] employ this concept and additionally introduce a communication protocol called NeurComm. It is similar to CommNet [25] but instead of summing the received messages, NeurComm concatenates them. Policy fingerprints supplement communication to reduce non-stationarity [28].

Representing each agent as a node in a network enables scaling to large agent populations. Yang et al. [29] propose employing this mean-field formulation to solve scalability issues. Accordingly, each agent is only affected by the mean effect of its local neighborhood. Compared to considering all agents, the complexity of interactions is reduced significantly for large agent populations. Decentralized neural actor-critic algorithm (Dec-Neural-AC) [30] is another mean-field approach aiming at scalability.

D. Centralized Training with Decentralized Execution

Modern MARL approaches often use centralization during training but create independent agents that run independently. This setting is known as centralized training with decentralized execution (CTDE). CTDE maps well to real-world use cases, where training can occur in simulation or with (potentially expensive) real-time communication, but agents should operate independently after training.

Usually, CTDE algorithms use an actor-critic architecture, which decomposes the policy and value estimates into explicit actor and critic networks. The critic is only used during training and to improve the policy's gradient updates. CTDE actor-critic algorithms exploit this by training multiple agents together with a shared critic. Only the independent actors are needed during execution, allowing agents to operate without communication after training.

Multi-agent deep deterministic policy gradient (MADDPG) [31] is an example of CTDE algorithms using per-agent actors with policy networks to map agent-specific observations to agent-specific actions. The critic approximates a centralized action-value function and receives the concatenated actions of all agents and additional global state information. This state information can include the concatenated observations of all agents. The agent's actions are included to make the environment more stationary [31].

Off-policy methods, such as MADDPG, were commonly considered to be more sample-efficient than on-policy methods. However, Yu et al. [32] propose the on-policy algorithm multi-agent proximal policy optimization (MAPPO) that performs comparably to off-policy algorithms. MAPPO suggests using global environment information as input to the critic instead of a concatenation of all observations, which scales with an increasing number of agents.

Recurrent Policy Optimization [33] is a recent method using a recurrent critic and a combinator that combines different agents' trajectories into one meta-trajectory. This meta-trajectory is used to train the critic and allows the approach to learning better from agents' interactions.

V. MARL IN AUTONOMOUS MOBILITY: APPLICATIONS AND CHALLENGES

Many real-world scenarios in autonomous mobility involve multiple agents. This presents an obvious potential for MARL approaches to optimize how agents cooperate and interact. Autonomous mobility scenarios face similar key challenges. Large agent populations cause scalability and credit assignment issues. As mobility scenarios are usually

highly dynamic, fast reaction times are required. We give an overview of application domains of MARL in autonomous mobility and discuss potential benefits, challenges, and recommendations for MARL-based methods. Table II lists different environments and their use-cases.

A. Traffic Control

Traffic congestion in cities is problematic as it causes pollution, financial loss and increases the risk of accidents [50]. Hence, controlling the traffic through traffic signals, line controls, or routing guidance has great potential to improve living conditions. Traffic involves many participants, including traffic lights, vehicles, and pedestrians. MARL is an obvious fit for the traffic control problem as it does not rely on limiting heuristics. Data from various sources, e.g., road surveillance cameras, location-based mobile services, and vehicle tracking devices can be input into MARL models [11].

Adaptive traffic signal control is a prominent approach to traffic control. A large number of agents, however, demand solutions to problems related to the scalability issue. As centralized and CTDE approaches do not scale well for large agent populations, decentralized approaches are an evident choice. However, convergence is not guaranteed (Section IV-A). To make the environment stationary from the agents' perspectives, Wang et al. [51] introduce graph attention networks to learn the dynamics of the neighbor intersection's influences. Instead of attention networks, Chu et al. [17] propose communication to the neighboring agents to improve the convergence of decentralized training. In addition, a spatial discount factor is used to weigh neighboring agents' observation and reward signals.

In essence, all approaches assume that neighboring agents are most relevant to controlling local traffic. However, training MARL models needs a lot of data, making the availability of accurate simulators crucial. SUMO [10] and CityFlow [11] provide macroscopic city-scale simulations that can efficiently model many different agents and their interactions.

B. Autonomous Vehicles

A different application directly controls multiple autonomous vehicles through MARL. Compared to independent single-agent RL [52], this improves the ability of agents to cooperate and achieve their individual objectives. In this domain, performance gains can come from coordinated driving (e.g., by reducing wind resistance, traffic jams, and optimizing road usage [28]), the ability to extend the own perception with information from other agents (through vehicle-to-vehicle (V2V) / vehicle-to-X (V2X) communication [53]), or through efficient interactions in intersection navigation scenarios [54].

A large variety of simulation and benchmark environments are available for research on autonomous vehicles. The Highway-Env [45] allows to control multiple vehicles and is particularly easy to set up and use. However, we found that performance can drop below acceptable levels for large-scale traffic simulations of many vehicles. BARK [43] is

TABLE II: Simulation environments for general-purpose MARL research and four application fields summarized in Sec. V. Environments are characterized by either partial (P) or full (F) observability. Action spaces can either be discrete (D) or continuous (C). Slashes (A/B) denote that the environment can be configured to have different characteristics.

Environment	Type	Obs.	Actions	Description
General Purpose				
MAgent ¹ [41]	Comp	P	D	Multiple environments with a large number of agents
Multi-Agent Particle ¹ [2]	Coop / Comp	P	D / C	Multiple environments focused on communication
Traffic Control				
CityFlow [11]	Coop / Comp	P / F	-/-	City traffic simulator
SUMO [10]	Coop / Comp	P / F	D / C	Traffic simulation
Autonomous Vehicles				
SMARTS ² [42]	Coop	P	C	Autonomous driving simulation platform
BARK ³ [43]	Coop	P / F	D / C	Autonomous driving scenarios
MACAD ⁴ [44]	Coop / Comp	P	D / C	Multi-Agent Connected Autonomous Driving built based on CARLA
highway-env ⁵ [45]	Coop	P / F	D / C	Autonomous driving and tactical decision-making tasks
Unmanned Aerial Vehicles				
Gym PyBullet Drones ⁶ [46]	Coop / Comp	P	C	Simulation environment for quadcopters with OpenAI gym API
AirSim ⁷ [47]	Coop / Comp	P	C	High-fidelity simulation environment for UAVs and autonomous vehicles
Resource Optimization				
MARO ⁷ [48]	Coop	P	D / C	Resource optimization in industrial domains
Flatland ⁸ [49]	Coop	P / F	D	Vehicle re-scheduling problem

¹ github.com/Farama-Foundation/PettingZoo

² github.com/huawei-noah/SMARTS

³ github.com/bark-simulator/bark-ml

⁴ github.com/praveen-palanisamy/macad-gym

⁵ github.com/eleurent/highway-env

⁶ github.com/utiasDSL/gym-pybullet-drones

⁷ github.com/microsoft/maro

⁸ flatland.aicrowd.com/intro.html

an open-source simulation framework for autonomous vehicle research focusing on multi-agent scenarios with interactions between agents. BARK simulates various traffic scenarios and has a two-way interface to control cars hosted in CARLA, a widely-used AV research simulation framework. Similarly, SMARTS [42] provides a simulation environment for diverse driving interactions, is compatible with the OpenAI gym interface, and offers multiple different observations.

This line of work presents unique challenges: Autonomous vehicles must act in dynamic and unpredictable environments like urban or highway traffic, and safety constraints must be satisfied at any time. This limits the exploration crucial for RL. Post-hoc extraction of safe policies trained in a simulator [52] can be used to assure safety, but these methods have not yet been successfully applied to complex, multi-agent control settings. Moreover, most MARL methods assume identical or compatible algorithms. This requires manufacturers to agree on a common architecture and communication standard to facilitate cross-brand cooperation of vehicles.

C. Unmanned Aerial Vehicles

Swarms of unmanned aerial vehicles (UAVs) are another popular application field. UAVs are especially beneficial for communication tasks [55] and applications where human lives are endangered. Here, a (potentially large) network of UAVs needs to be controlled to fulfill tasks like forest fire surveillance [56], road traffic monitoring, [57] and air quality monitoring [58]. Moreover, UAVs can be used to provide internet access in remote areas and enable wireless communication for applications like navigation and control [59].

Multiple works use MARL to plan paths and assign targets for UAVs, in a problem known as Multiple Target Assignment and Path Planning (MUTAPP). Here, MARL-based

methods can outperform classical optimization techniques, like mixed-integer linear programming, because they can handle dynamic environments and operate in a decentralized way [60]. Qie et al. [60] propose a solution based on MADDPG to jointly optimize target assignment and path planning. They propose a task abstraction layer that combines these tasks into a common reward structure. Their algorithm can effectively minimize the number of conflicts that arise in the MUTAPP problem.

In general, UAVs present a challenging problem for almost all algorithms. Typical environments for UAVs are highly dynamic [60] and require constant collision avoidance (and thus quick reaction times) between individual agents. In addition, UAVs have strict real-time constraints for their operation, which limits complex central path planning and possible architectures for MARL algorithms. [60]. Another major challenge is the energy supply and the limited range of UAVs. Jung et al. [61] apply a solution based on CommNet [25] to coordinate the assignment of UAVs to charging towers and to share energy between towers, optimizing power draw from the electrical grid and minimizing operational costs.

Most research on UAVs uses custom, low-fidelity environments to simplify development [60], [61]. However, multiple high-fidelity simulators are available that model UAV dynamics in more detail. AirSim [47] is a simulation platform based on the Unreal Engine with a special focus on realistic simulation and hardware-in-the-loop research. It supports detailed rendered camera observations. In addition to UAVs, AirSim is also able to simulate cars. Gym PyBullet Drones [46] presents a physical simulator for research on UAVs. In contrast to AirSim, Pybullet Drones features more realistic physical effects like the ground effect and downwash, and it is compatible with OpenAI gym and RLLib.

D. Resource optimization

In another line of work, MARL is applied to resource optimization and scheduling for mobility scenarios. This includes scheduling for trains [49] or ambulances, but also taxi repositioning [62] and ride-sharing services [63], bike repositioning, or container inventory management [48]. Li et al. [63] propose to solve the assignment of ride requests to specific drivers with MARL, which improves order response rates.

A popular simulation used in the train scheduling and routing domain is Flatland, which has been used in several NeurIPS competitions [49]. Flatland provides a 2D-gridworld of train tracks. Agents (i.e., trains) have to find optimal policies that are safe, performant, and robust to unforeseen circumstances since trains can break down. Observations can be global or local, and Flatland also allows custom observation spaces. The Multi-Agent Resource Optimization platform [48] provides simulations, an RL toolkit, and utilities for distributed computing for this domain. It supports diverse scenarios across multiple application domains, including the aforementioned container inventory management and bike repositioning tasks, and includes visualizations of these simulation environments.

VI. CONCLUSION

In conclusion, we would like to note several challenges and open problems in multi-agent reinforcement learning (MARL) research for mobility scenarios. Chief among these is a lack of explicit safety and interpretability affordances in almost all current algorithms. This introduces real risk in autonomous mobility scenarios, especially when autonomous vehicles or UAVs are controlled. Safe training and verification methods that certify policy safety [52], [64], [65] must be developed to deploy these methods in the real world [66].

A second challenge is integration with existing, manually controlled systems. This is evident in domains like traffic control or resource optimization, where human interaction and intervention (e.g., through emergency vehicles or manually prioritized resources) can come unexpectedly for agents that were only trained in a simulation. Effectively providing these interactions with human needs in simulation is an unsolved problem due to the low sample efficiency of RL.

Finally, most simulation environments assume perfect, high-bandwidth, latency-free communication. Despite recent advances in communication standards like 5G [53], [67], this is not a valid assumption in real-world scenarios. This makes more centralized solutions, like centralized training with decentralized execution (CTDE), harder or impossible to train in real-world situations. Recent methods that limit communication could be a possible solution to this problem.

Overall, however, MARL presents an exciting opportunity to learn solutions for complex problems involving multiple agents in an efficient, automated way.

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