Towards Self-Adaptive Resilient Swarms Using Multi-Agent Reinforcement Learning

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Abstract: Cooperative swarms of intelligent agents have been used recently in several different fields of application. The ability to have several units working together to accomplish a task can drastically extend the range of challenges that can be solved. However, these swarms are composed of machines that are susceptible to suffering external attacks or even internal failures. In cases where some of the elements of the swarm fail, the others must be capable of adjusting to the malfunctions of the teammates and still achieve the objectives. In this paper, we investigate the impact of possible malfunctions in swarms of cooperative agents through the use of Multi-Agent Reinforcement Learning (MARL). More specifically, we investigate how MARL agents react when one or more teammates start acting abnormally during their training and how that transfers to testing. Our results show that, while common MARL methods might be able to adjust to simple flaws, they do not adapt well when these become more complex. In this sense, we show how independent learners can be used as a potential direction of future research to adapt to malfunctions in swarms using MARL. With this work, we hope to motivate further research to create more robust intelligent swarms using MARL.

1 INTRODUCTION

Cooperative swarms play an important role in multiple applications in the modern world (Liekna et al., 2014; Dias et al., 2021). When we think about it, there is a wide range of different fields that come to mind: manufacturing, defence and security, agriculture, and healthcare, to name a few (Jahanshahi et al., 2017; Rodriguez et al., 2021; Hildmann and Kovacs, 2019; Hunjet et al., 2018). Swarms can be naturally seen in assembly lines in factories, or when considering human-machine cooperation in warehouses. In agriculture, it is common to see swarms of agents for smart applications (Qu et al., 2022), or in healthcare to monitor certain complex cases (Jahanshahi et al., 2017). In the context of defence, swarms of intelligent drones can be used to control certain areas and ensure better communication (Hunjet et al., 2018). Regardless of the field of application, it is always important to ensure that the systems are functioning properly. In other words, it is important to ensure that the elements in the swarm are performing as expected and are cooperating with the others.

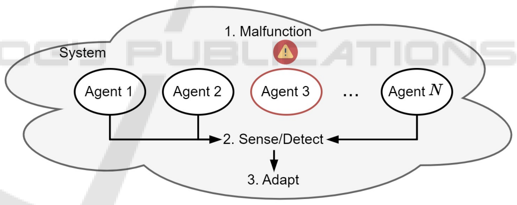

Figure 1: Illustration of the considered scenarios. When a malfunction affects the elements of a swarm, the remaining ones must be able to understand that and adapt.

Note the case of malfunctions that might occur in some of the elements of a certain swarm. These can be caused, for example, by external cyberattacks, by failures in a communication network, or even simply by internal unexpected flaws of one of the elements. These types of malfunctions can cause serious problems in the tasks that the swarm is trying to accomplish. If one of the entities is affected, it might also affect the performance of the rest of the swam, resulting in catastrophic consequences that could be avoided (Christensen et al., 2009; Revill, 2016). In this paper, we investigate precisely this problem, from a Multi-Agent Reinforcement Learning (MARL) perspective. MARL allows the devel-

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opment of extremely advanced and specialised behaviours within a swarm of cooperative agents (Albrecht et al., 2024). However, what if one of the agents incurs into a flaw? Are the other agents prepared to adapt to it? It is crucial that agents are capable of demonstrating this type of behaviour and are able to not only identify but also positively react to potential malfunctions of one or more of the elements of the swarm. In the case of such flaws, maintaining the good functioning of the swarm can prevent major consequences.

Along these lines, in this paper, we investigate scenarios where a swarm of agents attempts to solve a cooperative task. We aim to evaluate where the agents can naturally react to unexpected flaws in the behaviours of the teammates. In complex cases where they cannot adapt, we hypothesise a solution for them to adjust themselves and still be able to hold and perform reasonably until the others either recover or are replaced. Achieving this optimal behaviour can be key to address real problems where groups of agents need to improvise and react to unexpected situations where one of their reliable teammates incurs into an unforeseen impairment.

Overall, in this paper, we discuss potential problems that might occur within swarms and affect their performance holistically. As illustrated in Figure 1, when a malfunction incurs into one agent in a swarm, the others must understand that and adapt to it in order to still achieve their objectives. Through MARL, in this work, we delve into the implications of malfunctions in swarms and we identify future ways of research as a product of our results.

2 RELATED WORK

Swarms have been tipped to solve multiple emerging applications, including precision agriculture, search and rescue, disaster response and relief, surveillance and land administration and wildlife protection. In (Jurt et al., 2022), a swarm of warehouse robots was programmed to safely transport large and arbitrarily shaped objects towards a target direction that did not require prior knowledge of the object or the number of agents required. Some of these applications include very novel methods to address global challenges, such as climate change related scenarios. For example, a forest firefighting system based on the use of a swarm of hundreds of UAVs able to generate a continuous flow of extinguishing liquid on the fire front is conceptualised in (Ausonio et al., 2021).

In the same context of UAV swarms, to execute reconnaissance and strike tasks under insufficient enemy information and potential synergy between targets, a distributed task allocation method is proposed for heterogeneous UAV swarms in (Deng et al., 2023). The distributed system of the allocation of tasks does not depend on a highly reliable network nor a central node of control and thus improves the reliability and scalability of the swarm. In (Deng et al., 2023), all the task allocations and task executions are implemented as online optimisation and hardcoded heuristic algorithms for conflict resolution, negotiation and planning.

Most of the networked UAV swarm control methodologies are based on the mathematical model of flocking, in which three basic rules of, separation, alignment, and cohesion are simulated to achieve flocking-like behaviour. A model-free distributed intelligent controller is designed in (Jafari and Xu, 2018) to maintain the motion of all agents in the flock in the events of network-induced delay. The low complexity learning-based method is developed based on the computational model of emotional learning observed in the mammalian limbic system (Morén and Balkenius, 2000).

In (Hildmann et al., 2019), the authors addressed the scenarios where several UAVs are operating as a single functional unit, which is a swarm, to provide real-time data from their individual directed sensing equipment. The partial coverage from individual devices is to be combined with data from other devices to offer full coverage of a target object or area. This is a typical application of UAV swarms for surveillance such as reconnaissance, search and rescue, and data collection tasks such as precision agriculture. In the algorithm proposed in (Hildmann et al., 2019), a UAV swarm is able to autonomously adapt to changing resolution requirements for specific locations within the area under surveillance. The algorithm is inspired by how termites construct their nests, where without direct inter-agent communication, the members of a colony allow their decision-making to be guided by their environment.

In (Majd et al., 2020), the authors addressed the problem of safe and efficient routing of a swarm of drones through a parallel evolutionary-based swarm mission planning algorithm (Majd et al., 2020). Evolutionary computing allowed to plan and optimize the routes of the drones at run-time to maximize safety while minimising travelling distance as the efficiency objective.

Besides the biological-inspired approaches described, Reinforcement Learning (RL) has also been used in the context of swarms. For instance, in (Thumiger and Deghat, 2021) a MARL-based decentralised collision avoidance system in a swarm of homogenous agents is proposed, where a trained controller is tested in simulation and in a real-world 3-dimensional drone environment. Similarly, strategies in multi-UAV collaborative air combat scenarios can be learned through MARL (Li et al., 2022). MARL-based cooperative navigation of a swarm of UAVs is developed through MARL and Curriculum learning to facilitate and expedite convergence, under different task complexities.

With the potential threat of UAV swarms in modern battlefields, developing countermeasures against them as a form of defence has been studied. There are two broad categories of harming swarms: hard kill where the physical components are destroyed by means such as high-power RF signals that destroy UAV components, or soft-kill methods that employ hacking tactics to interfere with the robot's control mechanisms such as providing false navigation commands (Zhang et al., 2023). For example, when achieving cooperative flight by the swarm of UAVs, moments prior to it, the system is in a disordered state and vulnerable to a malicious attack. In (Zhang et al., 2023), authors develop countermeasures against a UAV swarm by developing a low intensity continuous radio inference scheme to degrade the communication between the drones.

Despite all the applications in swarms here mentioned, these are still liable to several threats to their normal behaviour and performance by means such as the ones described previously. Under such scenarios of attacks, the agents must still be able to recover and react accordingly to potential flaws. In this sense, in this paper, we investigate the robustness of swarm intelligence. Specifically, we are interested in dynamic behaviour learned through MARL and how agents react and adapt to potential malfunctions that might occur within their trusted swarm.

3 BACKGROUND

3.1 Decentralised Partially Observable Markov Decision Processes (Dec-POMDPs)

In this paper, we model our scenarios as Decentralised Partially Observable Markov Decision Processes (Dec-POMDPs). The reason to do so is because in most of the realistic scenarios involving swarms of agents they only have partial perceptions of the surroundings and cannot observe everything at any moment. Additionally, swarms naturally model interactions among agents. In our setting, we focus specifically on cooperative settings to evaluate how agents react to failures within their swarm.

Thus, we consider a problem defined by the tuple $G = (S, A, r, N, Z, P, O, \gamma)$, where S represents the state of the environment, from which each agent $i \in \mathcal{N} \equiv \{1, \ldots, N\}$ draws an observation $o_i \in O(s, i) : S \times \mathcal{N} \rightarrow Z$ at each timestep t. At each timestep, each agent chooses an action $a_i \in A$, forming a joint action $a \equiv a_1, \ldots, a_N$ that is performed at state s of the environment, resulting in a transition of state according to the probability function $P(s'|s, a) : S \times A \times S \rightarrow [0, 1]$, where s' is the next resulting state, and $\gamma \in [0, 1)$ is a discount factor. During learning, each agent i holds an observation-action history τ_i such that $\tau_i \in T = (Z \times A)^*$. The policies of the agents are conditioned on the respective history, $\pi(a_i|\tau_i) : T \times A \rightarrow [0, 1]$. At each timestep t the team receives a joint reward $r(s, a) : S \times A \rightarrow \mathbb{R}$, leading to the objective of finding a joint policy π that maximises the objective $Q_\pi(s_t, a_t) = \mathbb{E}_\pi[R_t|s_t, a_t]$, where $R_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k}$ is the discounted return.

3.2 Deep Reinforcement Learning

Reinforcement Learning (RL) has been around for some time (Sutton and Barto, 2018). One of the firstly proposed methods is named Q-learning (Watkins and Dayan, 1992). This algorithm follows the lines of dynamic programming and aims to learn an optimal Q-function that dictates the best actions to execute at each moment of a certain problem, based on its current state. The updates of the Q-function are made following the equation

$$Q(s, a) \leftarrow (1 - \alpha)Q(s, a) + \alpha(r + \gamma \max_a Q(s', a)). \tag{1}$$

However, working on the tabular case has limitations (Albrecht et al., 2024). For instance, tabular Q-learning cannot approximate states that it has not seen before, even if they are simply slightly different. Thus, in (Mnih et al., 2015) the authors have extended simple Q-learning to Deep Q-Networks (DQNs) that use deep learning approaches and hence are capable of learning outside of tabular settings. This extends drastically the range of problems that can be solved using reinforcement learning, allowing to learn an approximation for potentially infinite spaces. The DQN is trained to minimise the loss

$$\mathcal{L}(\theta) = \mathbb{E}_{b \sim B}\left[\left(r + \gamma \max_{a'} Q(s', a'\theta') - Q(s, a; \theta)\right)^2\right], \tag{2}$$

where θ and θ' are the parameters of a learning network and its target, respectively, and b is some sample sampled from a batch B.

Following the foundations of these approaches, the authors in (Tan, 1993) have demonstrated how

DQN can be used to train multiple agents independently, giving rise to one of the first MARL approaches. In this work, we explore cooperative environments that can be solved using MARL and use more complex recent approaches. Additionally, these also adopt recurrent DQNs in order to account for partial observability, as per (Hausknecht and Stone, 2015). In the experiments in this paper, we use independent learners that use recurrent DQNs. We refer to this method as Independent Deep Q-Learning (IDQL).

3.3 Value Function Factorisation in MARL

There are several types of methods in the literature of MARL suitable to solve cooperative problems such as the ones portrayed in this paper. Amongst them, we opt to focus on value function factorisation methods (Sunehag et al., 2017; Rashid et al., 2020; Pina et al., 2022). The key idea of these methods is to learn an efficient decomposition of a joint Q-function into a set of individual action-value functions. This allows the agents to have partial access to the policies of the others during training, but they execute actions in the environment following only their individual policy functions.

Thus, we can summarise this decomposition process as the following:

$$Q_{tot}(\tau, a) = f(Q_1(\tau_1, a_1), \dots, Q_N(\tau_N, a_N)), \quad (3)$$

where f represents a function (neural network) that learns a mix that should adhere to a factorisation condition named Individual Global-Max (IGM). This condition can be defined as

$$\underset{a}{\operatorname{argmax}}\, Q_{tot}(\tau, a) = \begin{pmatrix} \operatorname{argmax}_{a_1} Q_1(\tau_1, a_1) \\ \vdots \\ \operatorname{argmax}_{a_N} Q_N(\tau_N, a_N) \end{pmatrix} \quad (4)$$

In our experiments, we make use of QMIX (Rashid et al., 2020), one of the most popular value function factorisation methods in the MARL literature. This method complies with the IGM condition in (4) due to a structural constraint inherent to its factorisation process, referred to as a monotonicity constraint, defined as $\frac{\partial Q_{tot}(\tau,a)}{\partial Q_i(\tau_i,a_i)} > 0, \forall i \in \{1, \dots, N\}$. Intuitively, this means that the joint and all individual functions should be evolving in the same direction (Rashid et al., 2020).

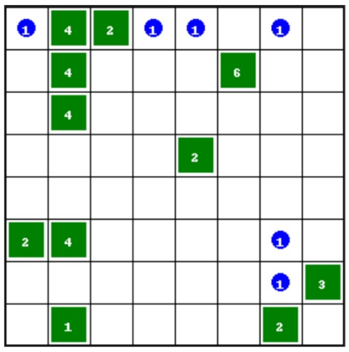


Figure 2: Lumberjacks environment with 6 agents (blue circles). The number inside the green squares represents the level of the tree, i.e., the number of agents needed to cut it.

4 METHODS AND SETTING

To evaluate our hypothesis, we use MARL with the objective of studying the level of robustness of swarm intelligence. Specifically, we intend to investigate the issue of malfunctioning agents within a swarm of cooperative agents, i.e., all agents expect every other agent to cooperate in a given task, but, in the case of malfunction, the agents should understand to ignore the potentially malicious agents. The objective is that the resultant agents are robust for the perturbations caused by an individual or a subset of malfunctioning agents.

4.1 The MARL Environment

The environment used in the experiments is named Lumberjacks and, in this environment, a team of 6 agents must learn cooperative strategies in order to cut all the existing trees in the world of the map (Figure 2). Every time a tree is cut, there is a reward of +5 for each agent. Note that these rewards are then summed and given as the team reward that is shared by the agents. The task becomes challenging because each tree has a pre-defined assigned level that dictates the number of agents needed at the same time to cut that specific tree. Logically, this requires their cooperation as a group. In addition, there is a step penalty of –0.01 that is given to each agent at every time step until the end of the episode. The episode terminates either when all the trees are gone or when a limit of 100 timesteps is reached. Logically, the higher the number of agents cooperating, the higher will be the reward received by the team.

4.2 Experimental Setup

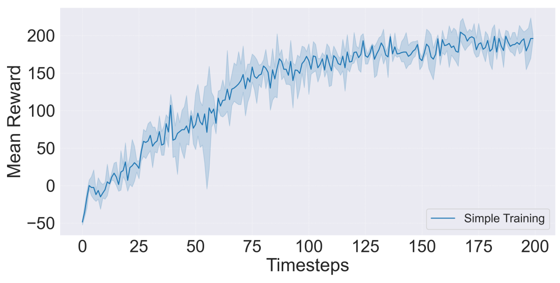
To evaluate our hypothesis, we design an experimental setup that consists of two main stages: 1) training the MARL agents in the described environment without any changes and 2) testing the learned policies in the same environment but one of the agents of the team starts executing random actions instead of following the learned policy (agent malfunction). Additionally, to test the hypothesis, we also train a variation of the training stage 1, where part of the agents fail during training, that is, part of the agents start executing random actions at a certain interval during training. We refer to this training scheme as Adaptive Training. With this additional experiment, we intend to investigate whether we can train the agents to anticipate during training these kinds of unexpected situations of system failures. In all the experiments we use the centralised training decentralised execution (CTDE) method QMIX, as described in section 3.3.

5 EXPERIMENTS AND DISCUSSIONS

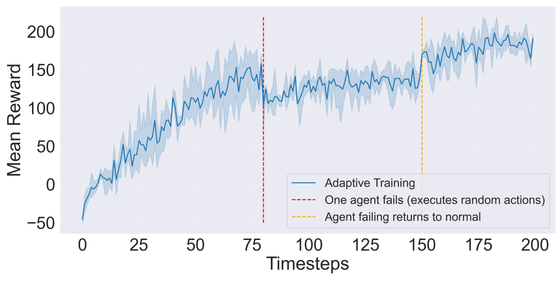
With the experiments presented in this section we intend to evaluate the following hypothesis: if we train a team of *N* MARL agents to solve a certain cooperative task, the team will struggle to re-adapt if one or more of the *N* elements start acting unexpectedly after the entire team is trained (that is, at evaluation/testing time).

5.1 Main Results

Figure 3 illustrates the results of the experimental stage 1 (as described in section 4.2). We can see that the agents can achieve a high reward in this task when they are trained using a strong MARL algorithm such as QMIX (Figure 3(a)). However, when we move the learned policies to the second stage (testing, as described in section 4.2), we can see that the induced changes in the scenario have an impact on the agents' behaviour (Figure 4). By looking at Figure 4, we observe that, while the agents still perform at a high level under normal conditions, when we make one agent act randomly the performance of the team decreases substantially. This raises the need for creating intelligent agents that are capable of actively reacting to these kinds of unexpected events. For instance, in certain real scenarios that require multi-agent cooperation, if there is a system malfunction in one of the agents, the remaining agents should be able to react to the prob-



(a)



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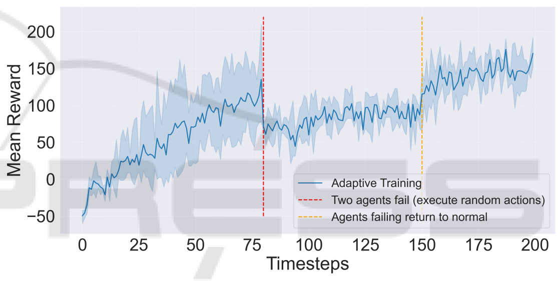


(c)

Figure 3: Training rewards over 2M timesteps. From top to bottom, (a) shows the performance of QMIX in an environment without malfunctions. (b) shows the performance of QMIX but during a period of timesteps (800k-1M) **one** agent acts randomly. (c) show the performance of QMIX but during a period of timesteps (800k-1.5M) **two** agents act randomly.

lem and adapt to the failure that occurred within the team.

Conversely, when we introduce one failure during the training of the team (Figure 3(b)), we can see that, although during training there is a break of performance that concurs with the moment of the introduction of the failure, the team will be better prepared to react to unexpected failures during the evaluation time (second stage) (Figure 4). Figure 3(b) shows a performance decrease from the moment of the introduction of a failure until roughly the moment when the agent recovers, that is, when the malfunctioning agent stops doing random actions and returns to acting according to the policy being learned. From the moment the failure ends, the team ends up achieving the same optimal performance as achieved by the

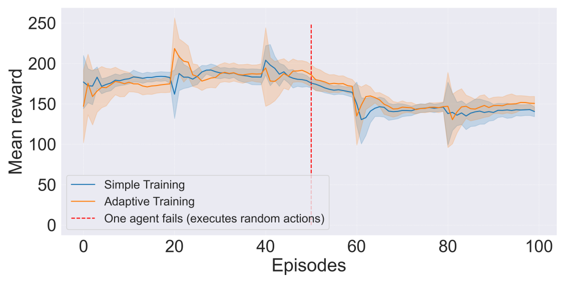


Figure 4: Evaluation of the agents over 100 episodes, but after 50 episodes one of the agents starts doing random actions (failure).

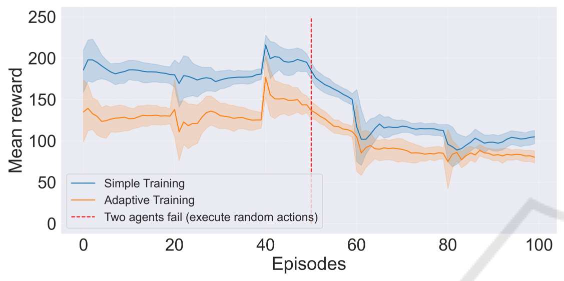


Figure 5: Evaluation of the agents over 100 episodes, but after 50 episodes two of the agents start doing random actions (two failures).

normal training as depicted in Figure 4. When the learned policies are transferred to the evaluation phase (stage 2), we can see that the team demonstrates good behaviour not only under normal environment conditions but also when a failure is introduced during the evaluation phase. When compared to the policies naively trained, the policies trained that encountered a failure during training achieve the same performance under normal conditions. Importantly, these policies also allow to improve the reward received when a failure occurs in the system. The presented results enforce the need for training more conscious agents in MARL that can react to unexpected failures in the elements of the team and still be capable of operating successfully when the others fail.

5.2 Additional Experiments

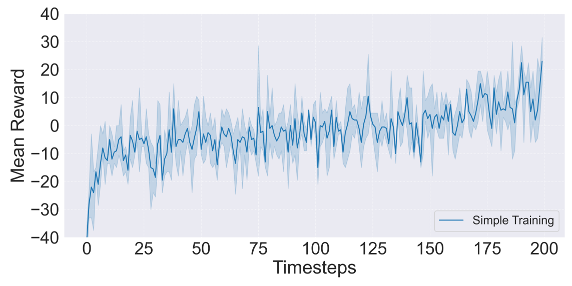
To further investigate our hypothesis, we extend the experiments carried out in the previous section to make two agents fail instead of only one. Following the same logic, we evaluate the performance of the agents trained under normal conditions in this setting (Figure 3(a)) and the performance of agents that have experienced the failure of two agents during training (as depicted in Figure 3(c)). While during training the evolution of the rewards achieved over time is similar to the previous experiments, Figure 5 shows that, when we evaluate the agents after training in a scenario where two elements fail, the rewards achieved decrease substantially for both training methods (normal and adaptive with two failures). In fact, the adaptive training that has seen two failures during training seems to be even more affected in this case, as opposed to the results with only one failure in Figure 4.

This observation suggests that the occurrence of two failures during training becomes confusing for the agents when learning the task as a team. This opens space for further research on how we can create more robust methods that are capable of accounting for an arbitrary number of failures and still perform well.

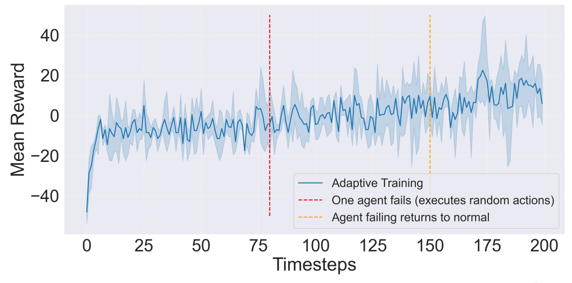
5.3 Results with Independent Learners (IDQL)

We have seen in the previous sections how the training phase of QMIX method is drastically affected when there is a malfunction in some of the agents of the swarm. We hypothesise that this performance drop can be due to the mixer of this method that is described in section 3.3. Since some of the agents incur into failures and perform random actions, the factorisation process during the centralised stage will be affected. This leads us to think that, one step towards improving reactions to these failures can be to use fully independent learners instead of using a mixer during a centralised step.

In Figure 6 we demonstrate the results for the same scenario, but now using fully independent learners (IDQL, as described in section 3.2). That is, these agents are trained in a fully decentralised and independent manner, by simply updating their Q-networks following the loss in (2). As the figure shows, the significant drops in performance during training that we observed in the previous figures do not exist anymore. Now, the performances are somewhat consistent between normal training (Figure 6(a)) and training with malfunctions of the agents (one malfunction in Figure 6(b) and two in Figure 6(c)). However, it is important to note that the rewards achieved in this case are far from being optimal. With the previous method, the agents can achieve much higher rewards in the task, meaning that, despite naive independent learners seeming to be more robust to malfunctions within the team, they are still not good enough to optimally solve complex tasks such as the one hereby presented. Thus, these insights highlight the need to develop stronger methods that can act in a fully independent manner. Novel strong independent methods can in fact be key to solve complex tasks, providing improved robustness at the same time.



(a)



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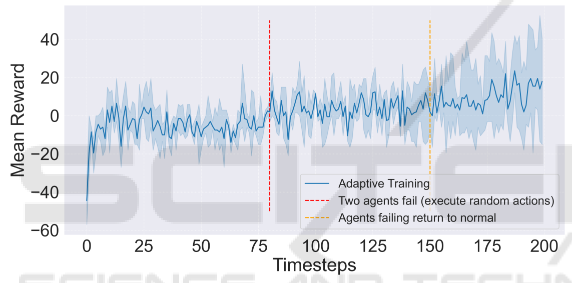

(c)

Figure 6: Training rewards over 2M timesteps. From top to bottom, (a) shows the performance of IDQL in an environment without malfunctions. (b) shows the performance of IDQL but during a period of timesteps (800k-1M) **one** agent acts randomly. (c) show the performance of IDQL but during a period of timesteps (800k-1.5M) **two** agents act randomly.

6 CONCLUSION AND FUTURE WORK

Swarms of intelligent agents are becoming increasingly popular in diverse applications. Despite their notorious advantages, they are still subject to potential attacks or internal flaws that they may not be able to control. Creating robust units that can positively react to these malfunctions can be key to developing stronger cooperative swarms.

In this paper, we investigated the effect of malfunctions within a trusted swarm of agents from a cooperative MARL perspective. We demonstrated that agents may not recover when some of their teammates incur into failures and start acting abnormally. While the proposed training scheme seems to be robust to simple failures (one agent), when these become more complex, it fails. Our results show that using independent learners can be a solution to create more resilient agents, but these may not be good enough to learn complex tasks properly. This motivates further work to find a middle ground between independent learners and other non-independent complex methods that can be both resilient and solve complex problems.

Along these, it is important to train entities that can not only find the patterns that correspond to potential malfunctions within their trusted swarm but are also able to react and adapt to them. With our results, we hope to motivate further research in this matter. In the future, we intend to further investigate this problem by creating more robust independent agents. Additionally, we aim to test these methods in real scenarios.

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