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C. G. Corlu, S. R. Hunter, H. Lam, B. S. Onggo, J. Shortle, and B. Biller, eds.

SIMULATION-BASED RESOLUTION OF DEADLOCKS IN AUTOMATED GUIDED VEHICLES USING MULTI-AGENT REINFORCEMENT LEARNING IN INTRALOGISTIC

Mustafa Jelibaghu

Technische Hochschule Aschaffenburg
Würzburger Straße 45
Aschaffenburg, 63743, GERMANY

ABSTRACT

This abstract presents a novel approach to address deadlock scenarios in automated guided vehicle systems utilizing Multi-Agent Reinforcement Learning (MARL) within a simulation framework. Deadlocks, frequently encountered in automated guided vehicles (AGVs) operations, impede system efficiency. Traditional resolution methods can be complex and suboptimal. This study proposes a MARL-based solution, capitalizing on the decentralized decision-making process of agents to navigate AGVs out of deadlocks. A simulated environment accurately mimics real-world AGV dynamics, enabling agents to learn deadlock resolution strategies through trial and error. The results demonstrate that the MARL approach significantly mitigates deadlocks, enhancing overall system performance. This research contributes to the synergy between simulation, multi-agent systems, and reinforcement learning, offering an efficient deadlock resolution paradigm with potential real-world AGV application.

1 INTRODUCTION

Deadlocks are a common problem in intralogistics systems, where multiple AGVs must coordinate their movements to avoid blocking each other. A deadlock occurs when two or more AGVs are waiting for each other to move, and neither AGV can move until the other AGV moves. This can lead to a situation where the AGVs are stuck in place and cannot complete their tasks.

Traditional deadlock resolution methods, such as deadlock avoidance and deadlock detection, can be inefficient and complex. Deadlock avoidance methods try to prevent deadlocks from occurring in the first place by ensuring that no two AGVs can ever be in a position to deadlock each other. Deadlock detection methods try to detect deadlocks as soon as they occur and then resolve them.

Reinforcement learning (RL) is a type of machine learning that allows agents to learn how to behave in an environment by trial and error. In the context of deadlock resolution, RL agents can be trained to learn how to avoid deadlocks by observing the states of the system and taking actions that lead to desired outcomes.

2 RELATED WORK AND SIMULATION MODEL

There has been a growing interest in using RL for deadlock resolution in intralogistics systems. In (Müller et al. 2022; Jelibaghu et al. 2023), the authors proposed a deadlock resolution method using a single RL agent. The agent was trained to learn how to resolve deadlocks by observing the states of the system and taking actions that lead to desired outcomes. The agent was able to achieve high levels of deadlock resolution and collisions avoidance in (Müller et al. 2022).

Our work builds on the work of (Müller et al. 2022; Jelibaghu et al. 2023). We propose a deadlock resolution method using a team of RL agents that is based on a real-world intralogistics system. We evaluate our method on a number of different scenarios, and we show that it is able to achieve high levels of deadlock resolution.

As part of the research project, a real application for an AGV system was considered and modelled in Plant Simulation (see Figure 1). The application is a high-bay warehouse with several aisles that the AGVs can only enter and exit from one side (dead ends). There are three AGVs available that have the task of moving pallets from the goods receipt, where the orders are created automatically and assigned to the AGVs (well known as dispatching), to the high rack. At the beginning the AGVs are located at the park station.

In Plant Simulation, the different strategies for detecting, avoiding and resolving deadlocks will be implemented and compared in terms of their performance. A deadlock situation is shown in Figure 1. The deadlock occurs because the AGV01 currently located on the STR02 wants to enter aisle02. At the same time, the AGV02 wants to leave aisle02.

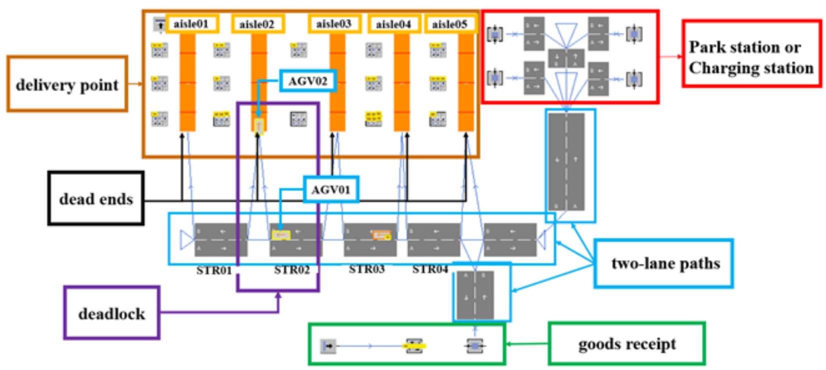

Figure 1: Illustration of a deadlock with three AGVs at the beginning of dead ends.

The simulation model is a digital twin of the logistics system, allowing for experimentation with different scenarios and the optimization of system performance. The model can simulate the movement of materials through the system and track the performance of different components, such as AGVs and conveyor systems. This can help identify potential bottlenecks and areas for improvement.

In conclusion, the simulation model developed in Plant Simulation and Python provides a powerful tool for evaluating the effectiveness of different algorithms in resolving deadlocks in AGV systems. The illustrations generated from the results of the simulation model provide valuable insights into the performance of the system and the potential benefits of using reinforcement learning techniques in the optimization of decision-making processes in complex dynamic environments (Sutton and Barto 2015).

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