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SOLVING DEADLOCK SITUATIONS IN INTRALOGISTICS WITH REINFORCEMENT LEARNING

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ABSTRACT

Intralogistics faces challenges from global disruptions such as the COVID-19 pandemic, geopolitical tensions, and wars, emphasizing the need for increased flexibility of logistic systems. Compounded by staff shortages in industrial countries, automation continues to rise, evidenced by the growing number of industrial robots. This rise in automation demands enhanced capabilities for intralogistic systems, including handling deadlocks. This research delves into the potential of reinforcement learning (RL) in addressing deadlocks, aiming to increase the efficiency, flexibility, and resilience of intralogistic systems.

1 PROBLEM AND MOTIVATION

The recent disruptions in global supply chains serve as a testament to the challenges faced by intralogistic systems. As the trend towards automation grows, partly driven by labor shortages, there's a heightened emphasis on maintaining consistent and efficient operations. This encompasses multiple facets, including the prevention of collisions and the management of deadlocks. Deadlocks pose a potential risk to system operations if not adequately addressed (Coffman et al. 1971).

Previous strategies for dealing with deadlocks in intralogistic systems are often based on rule-based or heuristic approaches. These approaches can reach their limits when confronted with the increasing complexity and dynamics of modern intralogistic systems. Rule-based approaches require comprehensive knowledge of all possible states and events in the system (Lienert and Fottner 2017), which is often impractical given the complexity of modern systems. While heuristics can provide an efficient solution for certain scenarios (Mayer and Furmans 2010), their performance can vary greatly in other contexts and they are often unable to adapt to changing conditions. In addition, the right choice of strategy to deal with deadlocks is strongly influenced by environmental parameters. Preliminary work shows that parameters such as the number of vehicles (Müller et al. 2020) or general disturbances (Müller et al. 2021) can make the initial strategy approach no longer appear optimal.

In this context, machine learning techniques, and in particular reinforcement learning (RL), offer a promising approach to addressing these challenges. Machine learning methods can recognize patterns and correlations in large amounts of data and derive predictions and decisions from them. Reinforcement learning, a form of machine learning, goes one step further and enables systems to learn and continuously improve their performance by interacting with their environment.

2 METHODOLOGY

This research delves into the application of reinforcement learning for deadlock handling with the goal of significantly elevating the efficiency, flexibility, and resilience of intralogistic systems. The main objectives are detailed below:

- **Systematic Approach for Deadlocks:** This objective seeks to intricately incorporate considerations for deadlocks during the planning phase of intralogistic systems, ensuring that potential system halts are anticipated and counteracted in advance.
- **Learning Environment Models:** Central to the successful deployment of reinforcement learning is the creation of conducive learning environments. This research focuses on designing and enhancing models that serve as adaptive and realistic learning environments for reinforcement learning algorithms, simulating real-world intralogistic scenarios with possible deadlock situations.
- **Tailored Reinforcement Learning Application:** Reinforcement learning algorithms hold vast potential, but their efficacy is tied to their customization. This objective is dedicated to the meticulous application and subsequent rigorous evaluation of reinforcement learning algorithms.

In order to achieve these objectives, the research explores several questions:

1. How can RL algorithms be applied to handle deadlocks in intralogistic systems?
2. How should intralogistic systems be modeled to be suitable as a learning environment for RL algorithms?
3. What specific properties and dynamics of intralogistic systems affect the efficiency of RL algorithms?
4. How can RL algorithms be optimized to achieve optimal performance in various intralogistic contexts?
5. How does the performance of RL algorithms compare to traditional deadlock-handling approaches?
6. How can RL algorithms be integrated into existing intralogistic systems and operational processes?

3 RESULTS

Preliminary findings suggest that RL algorithms can be effectively utilized in intralogistic systems that are susceptible to deadlocks. The RL algorithms primarily mitigate collisions in the early stages of the process. Nonetheless, they encounter hurdles in maintaining consistent high throughput rates. This is due to the tendency of RL algorithms to be excessively cautious to circumvent potential deadlocks or collisions. Subsequent implementations are expected to lead to enhancements in this area.

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