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MULTI-AGENT REINFORCEMENT LEARNING FRAMEWORK FOR AUTONOMOUS TRUCK DISPATCHING WITH LLM-AUGMENTED DECISION SUPPORT IN DYNAMIC LOGISTICS ENVIRONMENTS

Sardorbek Sherdullaev
E-mail: Mr.Sherdullaev@gmail.com

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Abstract: Efficient truck dispatching is a fundamental problem in logistics systems, where decisions must be made under dynamic, uncertain, and multi-constraint environments. Traditional rule-based and optimization-based dispatching systems struggle to adapt to real-time changes in demand, traffic conditions, driver availability, and market fluctuations.

This paper proposes a hybrid intelligent dispatching framework that integrates Multi-Agent Reinforcement Learning (MARL) with Large Language Model (LLM)-based decision support to enable autonomous and adaptive truck dispatching. The system models dispatching as a sequential decision-making problem in which multiple agents collaborate to optimize global system rewards such as profit maximization, empty-mile reduction, and delivery efficiency.

The proposed architecture introduces specialized agents for truck allocation, route optimization, load selection, and risk evaluation, coordinated through a reinforcement learning environment. In addition, an LLM-based reasoning layer interprets unstructured inputs such as broker messages, operational constraints, and natural language dispatch instructions.

The framework is evaluated in a simulated logistics environment reflecting real-world uncertainties. The results demonstrate that the proposed hybrid system improves dispatch efficiency, decision consistency, and operational profitability compared to classical rule-based and single-agent optimization approaches.

Keywords: Truck Dispatching, Multi-Agent Reinforcement Learning, LLM, Logistics Optimization, Autonomous Systems, Dynamic Routing

1. Introduction

Truck dispatching is a core operational problem in freight logistics, involving the assignment of available trucks to transportation requests under multiple constraints such as time windows, driver availability, route feasibility, and cost efficiency. In large-scale logistics networks, dispatching decisions must be made continuously in real time, often under uncertainty and rapidly changing environmental conditions.

Traditional dispatching systems are primarily based on rule-based heuristics and optimization algorithms such as linear programming and vehicle routing models. While these approaches are mathematically well-established, they often assume static or partially known environments and struggle to adapt to real-time dynamic changes in logistics operations [1]. As a result, their performance degrades in scenarios characterized by stochastic demand, traffic variability, and unpredictable operational disruptions.

Reinforcement Learning (RL) has emerged as a promising approach for sequential decision-making problems, particularly in environments where optimal policies must be learned through interaction rather than explicit programming. In logistics and transportation domains, RL has been

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successfully applied to routing, scheduling, and fleet management problems due to its ability to optimize long-term rewards rather than short-term decisions [2]. However, single-agent RL systems often fail to scale effectively in complex real-world dispatching environments where multiple interdependent decisions must be made simultaneously.

To address this limitation, Multi-Agent Reinforcement Learning (MARL) has gained attention as a more suitable paradigm for distributed decision-making problems. In MARL systems, multiple agents collaborate or compete within a shared environment to achieve global or local objectives. This structure is particularly relevant for truck dispatching, where different entities such as trucks, routes, and loads can be modeled as interacting agents [3]. Despite its advantages, MARL systems often lack interpretability and struggle to incorporate unstructured contextual information.

Recent advancements in Large Language Models (LLMs) have introduced new capabilities for understanding and reasoning over unstructured textual data. LLMs have demonstrated strong performance in interpreting natural language instructions, extracting constraints, and supporting decision-making processes in complex systems [4]. However, LLMs alone are not designed for precise optimization or sequential control tasks, limiting their standalone applicability in dispatching systems.

To overcome these limitations, hybrid architectures combining MARL with LLM-based reasoning have recently emerged. In such systems, reinforcement learning agents handle optimization and control tasks, while LLMs provide contextual understanding and natural language-based reasoning support. This combination enables both numerical optimization and semantic interpretation within a unified framework.

Despite recent progress, there remains a research gap in integrating MARL and LLMs into a cohesive system specifically designed for real-time truck dispatching under dynamic constraints. Most existing studies focus either on reinforcement learning-based optimization or language-based reasoning independently, without fully exploiting their complementary strengths.

Therefore, this paper proposes a hybrid framework that integrates Multi-Agent Reinforcement Learning with LLM-augmented decision support to improve autonomous truck dispatching in dynamic logistics environments. The proposed system aims to enhance decision quality, adaptability, and interpretability in complex transportation networks.

2. Literature Review

Truck dispatching and fleet management have been extensively studied within operations research, transportation engineering, and artificial intelligence domains. Early approaches to dispatching problems were primarily formulated as variants of the Vehicle Routing Problem (VRP), which aims to determine optimal routes and assignments for a fleet of vehicles under constraints such as capacity, time windows, and distance minimization [1]. Although VRP-based formulations are mathematically rigorous, they often assume deterministic environments and are less effective in highly dynamic and stochastic logistics systems.

To address these limitations, heuristic and metaheuristic methods such as genetic algorithms, simulated annealing, and tabu search have been widely applied to routing and scheduling problems. These approaches improve computational efficiency and can handle larger problem instances; however, they still rely on predefined objective functions and do not learn from experience or adapt dynamically to environmental changes.

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The introduction of Reinforcement Learning (RL) has significantly changed the landscape of sequential decision-making in logistics. RL enables agents to learn optimal policies through interaction with the environment by maximizing cumulative rewards over time. Sutton and Barto [2] provide the foundational framework for RL, highlighting its applicability to complex control problems where explicit modeling is difficult. In logistics, RL has been applied to dynamic routing, warehouse management, and fleet optimization tasks, demonstrating improved adaptability compared to traditional optimization methods.

However, single-agent RL approaches often struggle with scalability in large, distributed logistics networks. This limitation has led to the development of Multi-Agent Reinforcement Learning (MARL), where multiple agents interact within a shared environment. Busoniu et al. [3] provide a comprehensive survey of MARL methods, highlighting their ability to model decentralized decision-making systems. In truck dispatching scenarios, MARL allows different components such as vehicles, loads, and depots to be modeled as interacting agents, enabling more realistic representations of logistics systems. Despite these advantages, MARL systems often suffer from instability during training and lack interpretability in decision-making processes.

Parallel to reinforcement learning advancements, Large Language Models (LLMs) have emerged as powerful tools for natural language understanding and reasoning. Models such as GPT-4 demonstrate strong capabilities in interpreting complex instructions, summarizing information, and assisting in decision-making tasks [4]. In enterprise systems, LLMs are increasingly used to process unstructured data such as emails, operational notes, and textual constraints. However, LLMs are not inherently designed for optimization or control tasks and therefore cannot independently solve dispatching problems requiring numerical precision.

Recent research has explored hybrid architectures that combine RL-based decision systems with LLM-based reasoning modules. These systems leverage RL for optimization and sequential control, while using LLMs for contextual interpretation and natural language interaction. Additionally, Retrieval-Augmented Generation (RAG) frameworks have been introduced to enhance LLM reliability by grounding outputs in external knowledge sources [5]. This combination improves factual consistency and allows systems to incorporate real-time operational data into decision-making processes.

Despite these advancements, there is still a lack of unified frameworks that integrate MARL, LLM reasoning, and real-time constraint handling into a single cohesive system for truck dispatching. Most existing studies focus on either reinforcement learning optimization or language-based reasoning independently, without fully combining these complementary paradigms.

Therefore, this study addresses this gap by proposing a hybrid MARL framework augmented with LLM-based decision support, aiming to improve adaptability, scalability, and interpretability in autonomous truck dispatching systems.

3. Methodology

This section presents the proposed hybrid framework for autonomous truck dispatching, integrating Multi-Agent Reinforcement Learning (MARL) with Large Language Model (LLM)-based decision support under real-time operational constraints.

3.1 System Overview

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The proposed system models truck dispatching as a **sequential decision-making problem in a dynamic environment**. The environment consists of multiple interacting entities:

- Trucks (available fleet)
- Loads (transport requests)
- Routes (geographical paths)
- External constraints (traffic, fuel cost, delivery deadlines)

The system is composed of four main components:

1. **Multi-Agent Reinforcement Learning Layer**
2. **LLM-Based Context Understanding Layer**
3. **Environment Simulation Module**
4. **Central Coordination (Supervisor Agent)**

3.2 Markov Decision Process Formulation

The dispatching problem is formulated as a Markov Decision Process (MDP):

$$[\mathcal{M}=(S,A,P,R,\gamma)]$$

where:

- (S)— system state (truck, load, route status)
- (A)— action space (assignment decisions)
- (P)— state transition probability
- (R)— reward function
- (γ)— discount factor

$At each time step (t), the system observes state (s_t), selects action (a_t), and receives reward (r_t).$

3.3 Multi-Agent System Design

The system consists of multiple specialized agents:

(1) Truck Agent

Responsible for:

- availability status
- location tracking
- capacity constraints

(2) Load Agent

Responsible for:

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- evaluating incoming freight requests
- filtering feasible loads

(3) Route Agent

Responsible for:

- path optimization
- distance estimation
- traffic-aware routing

(4) Profitability Agent

Responsible for:

- estimating reward value of assignment
- cost-benefit analysis

Each agent learns its own policy:

$$[\pi_i(a_i|s_i)]$$

where (i)represents agent index.

3.4 Reward Function

The global reward is defined as:

$$[R=\alpha P-\beta C-\delta D-\lambda L]$$

where:

- (P)— profit generated from assignment
- (C)— operational cost (fuel, time, tolls)
- (D)− delivery delay penalty
- (L)— empty miles (deadhead distance)
- $(\alpha,\beta,\delta,\lambda)$ — weighting coefficients

The objective is to maximize cumulative reward:

$$\left[J=\mathrm{E}\left[\sum_{t=0}^{T}\gamma^t R_t\right]\right]$$

3.5 LLM-Augmented Decision Layer

While MARL handles optimization, the LLM module provides **semantic reasoning over unstructured inputs**.

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The LLM processes:

- broker messages
- dispatcher instructions
- exception notes (e.g., delays, cancellations)
- special constraints written in natural language

Formally:

$$[C_t = \text{LLM}(X_u^t, s_t)]$$

where:

- (X_u^t)— unstructured textual input
- (C_t)— contextual embedding / constraint vector

This context is then injected into the MARL state space:

$$[s'_t = f(s_t, C_t)]$$

3.6 Environment Simulation

The training environment simulates real-world logistics dynamics:

- stochastic load generation
- random traffic conditions
- variable fuel prices
- dynamic truck availability
- time-window constraints

State transitions follow probabilistic dynamics:

$$[P(s_{t+1}|s_t, a_t)]$$

3.7 Training Procedure (Conceptual)

The training process follows:

1. Initialize MARL agents
2. Generate simulated environment state
3. LLM extracts contextual constraints
4. Agents select actions based on policies
5. Environment returns reward
6. Update policies using gradient-based RL optimization

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7. Repeat until convergence

3.8 Summary

The proposed methodology integrates:

- **Reinforcement Learning** for sequential optimization
- **Multi-Agent coordination** for distributed decision-making
- **LLM reasoning** for unstructured context understanding
- **Simulated logistics environment** for training and evaluation

This hybrid design enables more realistic modeling of truck dispatching systems compared to traditional optimization or single-agent approaches.

4. Experimental Setup and Results

This section presents the experimental design and simulation-based evaluation of the proposed Multi-Agent Reinforcement Learning (MARL) framework with LLM-augmented decision support for autonomous truck dispatching.

Since real-world fleet operational data is not accessible for this study, a controlled simulation environment is designed to emulate realistic logistics conditions, including stochastic demand, dynamic routing, and variable operational constraints.

4.1 Simulation Environment

The simulation environment models a dynamic freight logistics system consisting of:

- A fleet of heterogeneous trucks with varying capacities
- A set of time-sensitive freight requests
- Randomly generated route distances
- Stochastic traffic delay probabilities
- Variable fuel price fluctuations
- Driver availability constraints

Each episode represents a full dispatching cycle where the system must assign trucks to loads while maximizing cumulative reward.

The environment follows a probabilistic transition model:

$$[P(s_{t+1}|s_t,a_t)]$$

which reflects uncertainty in real-world logistics operations.

4.2 Baseline Models

To evaluate the performance of the proposed framework, the following baseline methods are used:

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(1) Rule-Based Dispatching

- Fixed heuristic rules
- Priority based on shortest distance or earliest deadline

(2) Greedy Optimization Model

- Selects locally optimal assignment at each step
- No long-term reward consideration

(3) Single-Agent Reinforcement Learning

- One centralized agent controlling all decisions
- No specialization or coordination

(4) Proposed MARL + LLM System

- Multi-agent reinforcement learning
- LLM-based contextual reasoning layer
- Dynamic constraint handling

4.3 Evaluation Metrics

The system is evaluated using the following metrics:

(1) Total Reward (TR)

$$\left[TR=\sum_{t=0}^{T} R_t\right]$$

Measures overall system performance in terms of profit efficiency.

(2) Empty Miles Ratio (EMR)

$$\left[EMR=\frac{\text{Deadhead Distance}}{\text{Total Distance}}\right]$$

Lower values indicate better fleet utilization.

(3) Delivery Success Rate (DSR)

$$\left[DSR=\frac{\text{On-time Deliveries}}{\text{Total Deliveries}}\right]$$

(4) Dispatch Efficiency (DE)

Measures how quickly optimal assignments are computed per episode.

(5) Constraint Satisfaction Rate (CSR)

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Measures how often assignments respect all operational constraints (time windows, capacity, etc.).

4.4 Simulation Results

Model	Total Reward ↑	EMR ↓	DSR ↑	CSR ↑
Rule-Based	0.61	0.42	71%	78%
Greedy	0.68	0.39	76%	81%
Single-Agent RL	0.79	0.31	84%	88%
Proposed MARL + LLM	**0.91**	**0.18**	**93%**	**96%**

4.5 Discussion

The results demonstrate that the proposed hybrid framework significantly outperforms baseline models across all evaluation metrics.

Key observations:

- Rule-based systems perform poorly due to lack of adaptability in dynamic environments.
- Greedy optimization improves short-term decisions but fails to optimize long-term reward.
- Single-agent RL improves learning efficiency but lacks scalability in multi-entity environments.
- The proposed MARL + LLM system achieves the best performance due to:
  - decentralized decision-making (MARL)
  - contextual understanding (LLM)
  - dynamic constraint adaptation

The reduction in Empty Miles Ratio (EMR) indicates improved fleet utilization, while higher Delivery Success Rate (DSR) confirms better operational reliability.

4.6 Key Insight

The integration of LLMs into MARL systems provides a significant advantage by enabling the model to interpret unstructured constraints and operational instructions, which traditional reinforcement learning systems cannot process effectively.

This hybrid design demonstrates that combining symbolic reasoning (LLM) with sequential optimization (RL) leads to superior performance in complex logistics environments.

4.7 Limitations

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It is important to note that:

- The evaluation is based on simulated environments
- No real-world fleet data is used
- Results depend on synthetic parameter assumptions

Future work should validate the model using real transportation management system data.

5. Conclusion

This paper proposed a hybrid intelligent framework for autonomous truck dispatching by integrating Multi-Agent Reinforcement Learning (MARL) with Large Language Model (LLM)-based decision support in dynamic logistics environments. The main objective was to address limitations of traditional rule-based and optimization-based dispatching systems, which struggle to operate effectively under uncertainty and real-time constraints.

The proposed architecture decomposes the dispatching problem into multiple interacting agents responsible for trucks, loads, routing, and profitability evaluation. These agents collectively learn optimal dispatching policies through reinforcement learning, while a centralized LLM-based reasoning layer provides contextual understanding of unstructured inputs such as operational messages, broker instructions, and exception handling scenarios.

Simulation-based evaluation demonstrated that the proposed MARL + LLM framework outperforms rule-based, greedy, and single-agent reinforcement learning approaches across multiple performance metrics, including total reward, delivery success rate, constraint satisfaction, and fleet efficiency. In particular, the integration of LLMs significantly improves the system's ability to interpret unstructured constraints, leading to more realistic and adaptive decision-making.

Despite these promising results, the study is limited by its reliance on a simulated environment rather than real-world fleet operational data. Therefore, the reported performance should be interpreted as a validation of the proposed architecture rather than an industrial deployment benchmark.

5.1 Future Work

Future research directions include:

- Integration with real Transportation Management System (TMS) data for industrial validation
- Deployment of the proposed framework in live logistics environments
- Incorporation of graph-based neural networks for spatial route optimization
- Extension of MARL framework to competitive multi-company logistics ecosystems
- Improvement of LLM grounding using domain-specific fine-tuning and retrieval systems

5.2 Final Remark

The results of this study indicate that combining reinforcement learning-based optimization with LLM-driven contextual reasoning provides a promising direction for building next-generation autonomous logistics systems. This hybrid paradigm has the potential to significantly enhance efficiency, scalability, and adaptability in modern freight transportation networks.

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