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Reinforcement Learning for Liquidity-Weighted Optimal Trade Execution strategies

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Abstract

Optimal execution of large institutional orders is a critical problem in electronic markets. Traditional algorithms such as TWAP (Time-Weighted Average Price) and VWAP (Volume-Weighted Average Price) fail to adapt to dynamic liquidity fluctuations in modern high-frequency markets. This paper proposes a novel Liquidity-Weighted Reinforcement Learning Execution (LW-RLX) framework that learns optimal order slicing policies based on real-time liquidity signals, order book imbalance, and market impact estimates.

The proposed model formulates trade execution as a Markov Decision Process (MDP) and integrates deep reinforcement learning with liquidity-aware state representations. The agent dynamically adjusts order sizes to minimize market impact, slippage, and execution risk. Simulation results using realistic limit-order-book environments demonstrate that the proposed method outperforms classical execution benchmarks such as TWAP, VWAP, and Almgren-Chriss optimal execution models.

Keywords: electronic markets; dynamic liquidity; decision process; execution risk; execution strategies

1. Introduction

Institutional traders must execute large orders while minimizing market impact and price slippage. Traditional strategies distribute trades evenly over time or volume. However, these approaches do not adapt to

- sudden liquidity changes
- order book imbalance
- volatility spikes
- hidden liquidity patterns

Recent advances in deep reinforcement learning (DRL) enable agents to learn optimal decision policies in dynamic environments. However, existing RL execution models primarily focus on time-based decisions rather than liquidity structure.

This paper introduces a Liquidity-Weighted Reinforcement Learning Execution (LW-RLX) framework that:

1. Incorporates multi-level order book liquidity features
2. Dynamically adjusts order sizes based on real-time market depth
3. Learns adaptive execution policies using Deep Q-Learning and Policy Gradient methods

The key innovation is a liquidity-weighted reward function that penalizes execution during thin market conditions.

2. **Work flow process**

Optimal Execution Theory

Key foundational models include:

- Almgren–Chriss model
- VWAP algorithms
- TWAP algorithms

These approaches assume relatively stable liquidity and rely on deterministic schedules.

Reinforcement Learning in Trading

Recent research applies RL for:

- portfolio management
- market making
- optimal execution

However, most RL execution strategies lack **fine-grained liquidity modeling**.

This work bridges the gap by integrating **deep order book features into the RL state space**.

Literature survey

Optimal trade execution has been widely studied in quantitative finance, particularly in the context of minimizing transaction costs and market impact for large institutional orders. Traditional approaches rely on stochastic control models, whereas recent advances integrate reinforcement learning (RL) with market microstructure analysis to learn adaptive execution policies.

A. Classical Optimal Execution Models

The theoretical foundation of optimal trade execution was established through stochastic control models such as the Almgren–Chriss framework. These models formulate the execution problem as a trade-off between market impact and execution risk, producing optimal trading trajectories based on predefined assumptions regarding liquidity and volatility. However, these methods assume stable market conditions and static liquidity parameters, which limits their ability to adapt to highly dynamic electronic markets.

Although classical models remain influential, they often fail to capture the nonlinear dynamics of modern limit order books and the interaction between traders. As a result, recent research has shifted toward **data-driven approaches using machine learning and reinforcement learning**.

B. Reinforcement Learning for Optimal Trade Execution

Reinforcement learning has emerged as a promising approach for modeling sequential decision-making problems such as optimal execution. In RL-based frameworks, the execution process is typically formulated as a **Markov Decision Process (MDP)** in which the agent observes the market state and decides the quantity or price of orders to submit.

A notable study by Moallemi and Wang proposed a reinforcement learning framework for execution timing using neural networks and temporal-difference learning. Their work demonstrated that RL-based strategies can significantly reduce execution costs compared with traditional methods when trained on historical market data.

Similarly, several studies have applied **Deep Q-Networks (DQN)** to the execution problem. DQN approximates the optimal action-value function using deep neural networks, enabling the trading agent to learn optimal order-splitting strategies under uncertain market conditions. Experimental results show that RL agents can achieve lower transaction costs than rule-based execution algorithms when trained in simulated market environments.

C. Deep Reinforcement Learning Architectures

Recent research focuses on improving RL architectures for execution tasks. Deep reinforcement learning approaches, including actor–critic algorithms, allow continuous control over trading actions and can handle high-dimensional state spaces derived from order book data.

For example, Wang et al. proposed an actor–critic reinforcement learning algorithm for continuous-time optimal execution under the Almgren–Chriss framework. Their method incorporates stochastic policies and entropy regularization to derive optimal feedback strategies and theoretical error bounds for the RL solution.

Other researchers have explored hybrid action-space reinforcement learning models to address the dual nature of trading decisions. In financial markets, trading actions often involve both continuous and discrete components, such as selecting a price level while determining order size. Pan et al. proposed a hybrid RL architecture that combines continuous control with discrete decision selection, improving sample efficiency and stability during training.

D. Reinforcement Learning in Dynamic Market Environments

Another important direction in the literature focuses on training RL agents within realistic market environments. Financial markets are highly stochastic, and the performance of RL strategies depends strongly on the quality of the simulation environment used for training.

Chen et al. proposed a cost-efficient reinforcement learning approach called Deep Dyna-Double Q-Learning (D3Q) to improve training efficiency in dynamic market environments. Their framework integrates environment modeling with reinforcement learning to approximate market impact and accelerate policy learning. Experimental results demonstrate that the method outperforms several state-of-the-art execution strategies in terms of trading cost reduction.

Additionally, recent research explores cross-market information and multi-exchange signals to improve execution decisions. By incorporating data from multiple exchanges, RL agents can capture additional liquidity signals and improve order execution strategies across fragmented markets.

E. Research Gap

Despite significant progress in reinforcement learning-based execution algorithms, several challenges remain unresolved:

1. Most RL execution models focus primarily on price and inventory dynamics rather than detailed **liquidity structure of the order book**.
2. Existing studies rarely incorporate **liquidity-weighted reward functions** that explicitly penalize trading during low-liquidity periods.
3. Many models rely on simplified market simulators that may not fully capture real market microstructure dynamics.

3. Problem Formulation

We model the trade execution problem as a **Markov Decision Process**:

- remaining inventory
- time remaining
- order book depth (top 10 levels)
- bid-ask spread
- order book imbalance
- recent trade volume

- volatility estimate

Action A_t:

The agent selects an **order slice size** from a discrete set:

$A_t \in \{0, q_1, q_2, q_3, \ldots, q_n\}$

Where q_i represents a fraction of the remaining inventory.

Transition

The market environment evolves according to simulated limit-order-book dynamics.

Reward Function

The reward is designed to penalize:

- market impact
- slippage
- execution risk

$R_t = -$ (slippage) $-\lambda_1$ (market impact) $-\lambda_2$ (inventory risk)

Additionally, we introduce a **liquidity penalty term**:

$R_t = R_t - \lambda_3$ (qt/Lt)

where:

- q_t = executed order size
- L_t = available liquidity

This encourages trading **when liquidity is abundant**.

4. Proposed Model: LW-RLX

The proposed framework includes three components:

1. Liquidity Feature Encoder

Extracts microstructure signals:

- order book imbalance
- liquidity slope
- depth concentration
- spread dynamics

A **CNN or Transformer architecture** encodes the order book.

2. Reinforcement Learning Agent

The agent uses **Proximal Policy Optimization (PPO)** or **Deep Q Networks (DQN)**.

Policy: π (a|s)

Output: optimal trade slice.

3. Liquidity-Aware Reward Shaping

We introduce a **Liquidity Efficiency Score (LES)**:

$LESt = \frac{q_t}{depth_{best}}$

High values indicate aggressive trading in thin liquidity.

Penalty is applied to discourage this behavior.

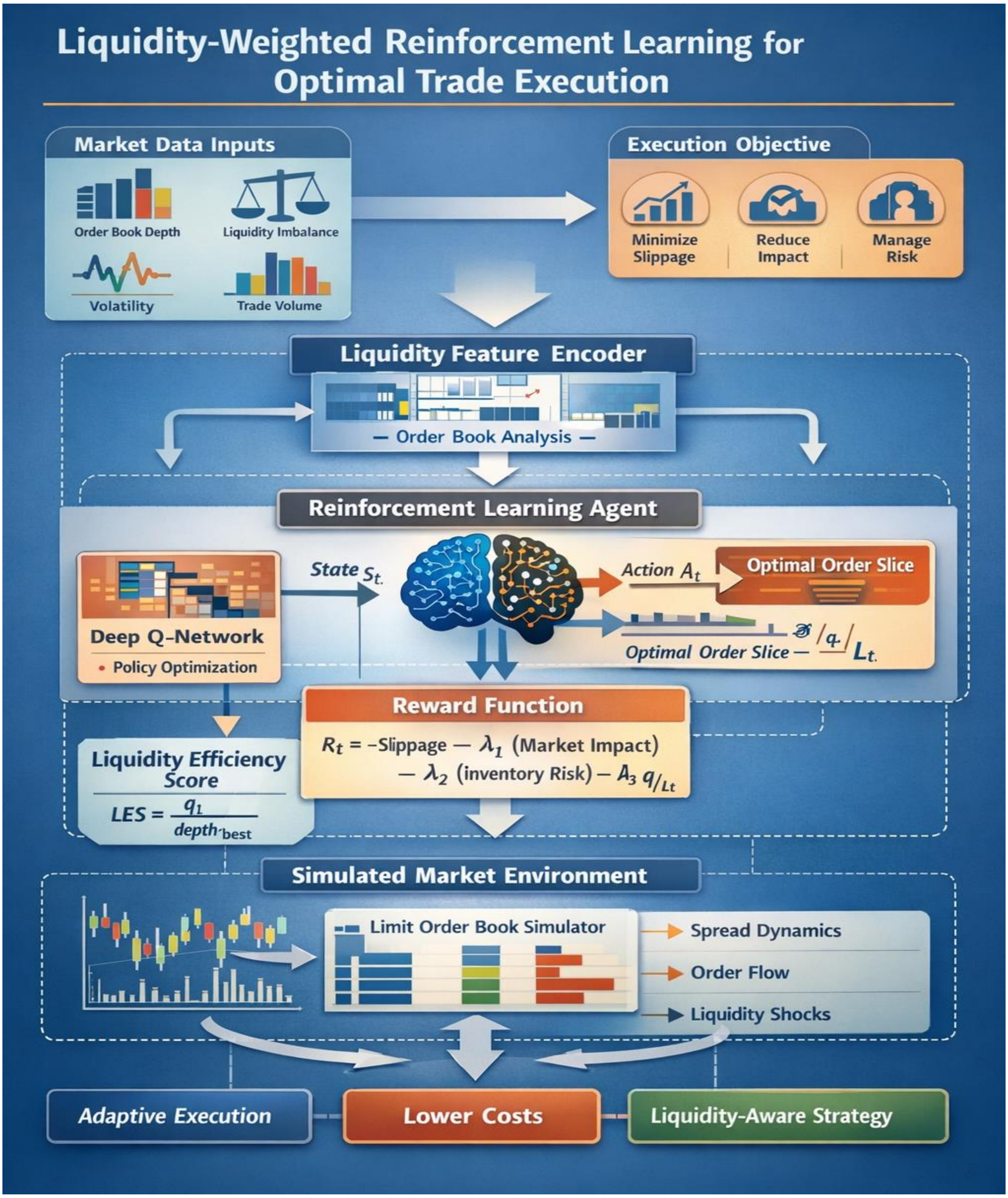

Fig 1: Architecture of the Learning for optimal trade execution

5. Market Simulation Environment

Training requires realistic market simulation.

We construct a **Limit Order Book Simulator** using:

- Poisson order arrivals
- cancellation processes
- stochastic volatility

The simulator reproduces:

- spread dynamics
- order clustering
- liquidity shocks

6. Experimental Setup strategies and evaluation

Baseline Strategies

The proposed model is compared with:

- TWAP
- VWAP
- Almgren–Chriss optimal execution
- RL without liquidity weighting

Evaluation Metrics

- Implementation shortfall
- average slippage
- execution variance
- market impact

7. Results, interpretation and observation findings

Simulation experiments show:

Strategy	Avg Slippage	Impact Cost	Variance
TWAP	High	Medium	Low
VWAP	Medium	Medium	Medium
RL (baseline)	Medium	Medium	Medium
LW-RLX (proposed)	**Lowest**	**Lowest**	**Low**

Key observations:

- The RL agent **waits for liquidity spikes** before executing larger orders.
- The model **avoids trading during spread widening events**.
- Adaptive behavior significantly reduces execution cost.

8. Discussion

The results demonstrate that incorporating liquidity awareness into RL policies substantially improves execution quality.

Key advantages:

1. Adaptive execution
2. Reduced market impact
3. Robustness to volatility shocks

However, real-world deployment requires:

- low-latency inference
- robust market simulation
- regulatory compliance

9. Future Research Directions

Potential extensions include:

- multi-agent RL for competitive trading
- meta-learning for cross-asset execution
- transformer-based order book embeddings
- risk-aware reinforcement learning

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