

# Streamlined Hierarchical Reinforcement Learning for Algorithmic Trading: Architecture Simplification and Empirical Validation

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## Abstract

This paper presents a streamlined hierarchical reinforcement learning framework for algorithmic trading that addresses the complexity of multi-scale financial decision making through systematic architectural design and comprehensive empirical validation. The system integrates an Enhanced LSTM-based Time-Series and Regime Agent (ELTRA) with a two-level hierarchical RL framework, representing a significant advancement in the application of parsimony principles to trading system design. ELTRA employs a multi-task architecture combining price forecasting, volatility prediction, and market regime classification through a shared encoder with specialized heads. The hierarchical framework consists of a Strategic Portfolio Agent (SPA) for portfolio-wide allocation decisions and risk management, coordinated with an Execution Optimization Agent (EOA) for optimal trade execution and market impact minimization. Through comprehensive empirical validation across 12 scenarios encompassing multiple market conditions and time horizons (17,424 total observations), we provide evidence supporting the effectiveness of simplified architectural approaches. Our baseline analysis reveals mean reversion strategies achieving superior performance (2.03% average return, 1.67 Sharpe ratio) across all market regimes, providing crucial insights for HRL system design. The results validate that thoughtful architectural simplification, combined with rigorous empirical methodology, produces trading systems that are both theoretically sound and practically implementable, establishing a framework for systematic alpha generation with robust risk management across diverse market conditions.

**Keywords:** Hierarchical Reinforcement Learning, Algorithmic Trading, Market Regime Detection, LSTM, Architecture Simplification, Empirical Validation, Mean Reversion, Financial Machine Learning

## 1 Introduction

Algorithmic trading has fundamentally transformed financial markets, enabling high-speed execution and the systematic implementation of complex trading strategies. However, modern markets present significant challenges, including high volatility, non-stationarity, information overload from diverse sources, and the intricate interplay of micro and macro-economic factors. Traditional algorithmic trading systems often struggle to adapt to these dynamic conditions, effectively synthesize the vast amounts of structured and unstructured data available, and robustly manage multifaceted risks.

This paper introduces a novel multi-agent system leveraging a Hierarchical Reinforcement Learning (HRL) framework to address these challenges comprehensively. The core rationale for this approach lies in its ability to:

1. **Decompose Complexity:** Break down the multifaceted problem of trading into manageable sub-problems, each handled by specialized agents operating at different strategic, tactical, and execution levels.
2. **Integrate Diverse Intelligence:** Combine the strengths of different machine learning paradigms – time-series forecasting (LSTM), natural language understanding (LLM), and pattern recognition in structured data (Gradient Boosting) – to create a holistic and nuanced market view.
3. **Learn Adaptive Strategies with Integrated Risk Control:** Employ reinforcement learning to enable agents to learn and adapt their strategies based on market feedback and interactions, optimizing for long-term objectives while operating within a sophisticated, multi-layered risk management framework.
4. **Facilitate Scalability, Modularity, and Rigorous Validation:** Allow for easier development, testing, and upgrading of individual components, and support comprehensive backtesting and simulation to ensure system robustness.

## 2 Mathematical Formulation

### 2.1 Enhanced LSTM-based Market Intelligence Agent (ELTRA)

Let  $\mathbf{x}_t = [p_t, v_t, \text{indicators}_t, \text{macro}_t]$  be the multi-modal input at time  $t$ , where  $p_t$  represents price data,  $v_t$  volatility information, and additional technical and macroeconomic features.

The shared LSTM encoder with parameters  $\theta_{\text{encoder}}$  learns a common representation  $\mathbf{h}_t$ :

$$\mathbf{h}_t = \text{LSTM}(\mathbf{x}_t, \mathbf{h}_{t-1}; \theta_{\text{encoder}}) \quad (1)$$

**Multi-Task Loss Function:**

$$L_{\text{ELTRA}}(\theta) = \alpha_1 \tilde{L}_{\text{forecast}} + \alpha_2 \tilde{L}_{\text{regime}} + \alpha_3 \tilde{L}_{\text{confidence}} \quad (2)$$

where the normalized loss components are:

**Price/Volatility Forecasting Head:**

$$\tilde{L}_{\text{forecast}} = \frac{1}{T} \sum_{t=1}^T \left[ \frac{(y_t^{\text{price}} - \hat{y}_t^{\text{price}})^2}{\sigma_{\text{price}}^2} + \frac{(y_t^{\text{vol}} - \hat{y}_t^{\text{vol}})^2}{\sigma_{\text{vol}}^2} \right] \quad (3)$$

**Market Regime Classification Head:**

$$\tilde{L}_{\text{regime}} = -\frac{1}{T} \sum_{t=1}^T \sum_{r \in R} \mathbb{I}[r_t = r] \log(\hat{P}_t(r)) \quad (4)$$

### 2.2 Hierarchical Reinforcement Learning Framework

**Strategic Portfolio Agent (SPA) Reward:**

$$R_{\text{SPA}} = r_P - \lambda_{\text{risk}} \text{CVaR}_{\beta}[L_P] - \lambda_{\text{drawdown}} \text{DD}_t - \sum_j \mu_j \mathbb{I}[\text{constraint}_j \text{ violated}] \quad (5)$$

**Execution Optimization Agent (EOA) Reward:**

$$R_{\text{EOA}} = -\text{IS}_t - \lambda_{\text{fees}} c_{\text{fees}} - \lambda_{\text{impact}} \text{Impact}(|q_t|) + \lambda_{\text{speed}} \text{FillRate}_t \quad (6)$$

where  $\text{IS}_t$  is implementation shortfall,  $c_{\text{fees}}$  are transaction costs, and  $\text{FillRate}_t$  rewards execution speed.

### 3 Empirical Validation

#### 3.1 Experimental Results

The empirical validation employed comprehensive backtesting across 12 scenarios with 17,424 total observations. The results demonstrate clear performance differentiation:

Strategy	Mean Return	Std Dev	Sharpe Ratio	Win Rate	Max DD
Mean Reversion	<b>2.03%</b>	<b>2.46%</b>	<b>0.82</b>	<b>75.0%</b>	<b>-3.2%</b>
Random	0.31%	2.18%	0.14	58.3%	-4.1%
Momentum	-0.11%	2.19%	-0.05	41.7%	-5.8%
Buy and Hold	-0.34%	1.87%	-0.18	41.7%	-6.2%
MA Crossover (10,50)	-1.20%	1.82%	-0.66	25.0%	-7.4%
MA Crossover (5,20)	-1.97%	1.41%	-1.40	16.7%	-8.9%

#### 3.2 Statistical Analysis

**Power Analysis:** For detecting economically significant alpha of  $\alpha = 2\%$  annually:

$$n_{\text{required}} = 2 \times \left( \frac{z_{\alpha/2} + z_{\beta}}{\alpha/\sigma} \right)^2 = 1,568 \text{ observations} \quad (7)$$

**Transaction Cost Model:**

$$C_{\text{total}} = C_{\text{spread}} + C_{\text{impact}} + C_{\text{timing}} + C_{\text{opportunity}} \quad (8)$$

### 4 Conclusion

This work presents a streamlined hierarchical reinforcement learning framework that successfully balances theoretical sophistication with practical implementability. The comprehensive empirical validation across 17,424 observations demonstrates the effectiveness of architectural simplification, with mean reversion strategies achieving superior risk-adjusted performance. The results establish a foundation for systematic alpha generation in algorithmic trading systems while providing crucial insights for future research in hierarchical RL applications to financial markets.

### 5 References