MacroHRL: A Hierarchical Reinforcement Learning Framework for Risk-Aware Portfolio Management with Drawdown Minimization

Neelesh Nayak
University of Waterloo
n4nayak@uwaterloo.ca

Peter Lian
University of Waterloo
plian@uwaterloo.ca

Tony Xia
University of Waterloo
t48xia@uwaterloo.ca

***Abstract*—Modern portfolio management requires dynamic strategies that adapt to shifting macroeconomic regimes while prioritizing capital preservation. This paper introduces MacroHRL, a two-level hierarchical reinforcement learning (HRL) framework engineered for robust risk mitigation and drawdown minimization. The high-level Meta-Controller, a Proximal Policy Optimization (PPO) agent, selects a market regime (Bull, Bear, Crisis, or Sideways) each quarter based on macroeconomic indicators (VIX, CPI, and Yield Curve). The low-level consists of four specialized PPO Sub-Controllers, each trained on regime-specific historical data to learn optimal daily allocation policies. By explicitly penalizing tail risk through a Conditional Value-at-Risk (CVaR) reward function, MacroHRL achieves superior risk-adjusted performance. Tested on out-of-sample data (2023–2025), MacroHRL demonstrates a significant reduction in maximum drawdown compared to a buy-and-hold SPY strategy, achieving an annualized return of 28.07% with a maximum drawdown of only -9.90%, establishing it as a highly effective framework for risk-sensitive institutional investment.**

I. Introduction

A. Motivation

Modern portfolio management entails optimizing returns while rigorously mitigating downside risk. Traditional approaches like Modern Portfolio Theory (MPT) [1] often fail during "black swan" events or rapid regime shifts where correlations break down. Although Reinforcement Learning (RL) has demonstrated potential in developing adaptive policies [2], [3], monolithic agents frequently encounter difficulties in generalizing across diverse market conditions, such as inflationary bear markets and low-volatility bull runs. This lack of specialization often leads to significant drawdowns during transitions. Our objective is to develop a framework that treats risk mitigation as a primary design principle, using a hierarchical structure to isolate and manage regime-specific risks.

With emerging applications in automated trading and institutional risk management, hierarchical reinforcement learning (HRL) plays an increasingly important role in modern financial engineering [4]. By decomposing the complex task of global portfolio optimization into manageable sub-tasks, HRL allows for a more granular and robust response to market volatility. This is particularly relevant in the current economic climate, where traditional diversification strategies have been challenged by high cross-asset correlations during periods of systemic stress. The ability to dynamically shift between aggressive growth and defensive preservation is a necessity for long-term capital appreciation.

B. Related Works

Hierarchical Reinforcement Learning (HRL) decomposes complex tasks into a hierarchy of simpler sub-tasks [5]. In finance, this allows a high-level policy to manage long-term strategy while low-level policies handle daily execution [4]. Recent work has explored various RL algorithms and their varying effectiveness given the large state space and uncertainty of financial markets [6].

One of the earlier approaches integrated a prediction module with generative adversarial data augmentation within a model-based RL algorithm, aiming to mitigate data scarcity through synthesized time-series [7]. In 2023, Zou et al. introduced a cascaded LSTM architecture, feeding extracted temporal features into a Proximal Policy Optimization (PPO) agent to capture richer dynamics [8]. Recently, Li and Hai in 2024 presented a multi-agent deep RL system that fuses standard market quotes with additional stock indices, highlighting the growing trend of incorporating diverse data sources into financial decision systems [9]. MacroHRL bridges these gaps by combining the strategic depth of HRL with a rigorous CVaR-based reward structure focused on tail-risk suppression [10]. Unlike previous works that often treat risk as a secondary constraint, MacroHRL embeds risk-awareness directly into the hierarchical decision-making process.

C. Problem Definition

We formulate portfolio management as a Hierarchical Markov Decision Process (HMDP) with a primary objective of drawdown minimization. The framework consists of a Meta-Controller and four specialized Sub-Controllers: Bull (π^{bull}), Bear (π^{bear}), Crisis (π^{crisis}), and Sideways (π^{sideways}).

Meta-Controller MDP: At the start of each quarter t, the Meta-Controller observes macroeconomic state s_t^{meta} and selects a Sub-Controller g_t. Its reward R_t^{meta} is the risk-adjusted return of the chosen policy over that quarter.

Sub-Controller MDP: The selected agent g_t manages the portfolio daily. On day k, it observes market state s_k^{sub} and

outputs weights a_k^{sub}. The daily reward R_k is explicitly designed for risk mitigation:

$$R_k = r_k^p - c \cdot \sum_{i=1}^{N} |w_{k,i} - w_{k-1,i}| - \lambda \cdot \text{CVaR}_\alpha(L_k), \quad (1)$$

where r_k^p denotes the portfolio return at time k, c is the transaction cost, and λ is a risk-aversion coefficient penalizing the CVaR of recent losses L_k. This formulation forces the agents to prioritize capital preservation over aggressive growth.

II. Methodology

A. Data and Preprocessing

We utilize daily price data for 8 major ETFs (SPY, QQQ, EFA, EEM, TLT, HYG, GLD, VNQ) from 2010 to 2025. Macroeconomic indicators (VIX, CPI, Yield Curve) are sourced from FRED. The model is trained on 2010–2022 data and tested out-of-sample on 2023–2025. All features are normalized to ensure stable training of the PPO agents [11]. We also incorporate rolling volatility and momentum features to provide the agents with a richer context of recent market trends. This multi-modal data approach allows the model to capture both price-action dynamics and broader economic shifts.

B. Regime Classification and Specialization

To minimize drawdowns, the system must recognize and react to high-risk environments. We employ a priority-based rule set grounded in established financial literature:

- **Crisis**: VIX > 30 and SPY 63-day drawdown $< -10\%$. A VIX level above 30 is widely recognized as a "shock" or high-stress regime [12], [13], while a 10% drawdown threshold is a standard benchmark for identifying significant market corrections and systemic crises [14].
- **Bear**: CPI YoY $> 5.5\%$ (and not Crisis). This threshold identifies high-inflation regimes where traditional equity-bond correlations often break down, necessitating specialized defensive positioning [15].
- **Sideways**: $20 \leq$ VIX ≤ 30 and $|$SPY 63-day drawdown$| < 8\%$. This range captures "warning" regimes characterized by moderate volatility and lack of clear trend [12].
- **Bull**: All other periods, representing low-volatility growth environments.

Each Sub-Controller is a PPO agent trained exclusively on its assigned regimes' historical episodes. This specialization ensures that the "Crisis" agent, for instance, learns defensive maneuvers that a general agent might ignore in favor of bull-market gains. By training on regime-specific data, we mitigate the "catastrophic forgetting" problem often seen in monolithic RL agents when they encounter rare but high-impact market events. This architectural choice is fundamental to the framework's ability to maintain stability during extreme market stress.

C. Hierarchical Control Flow

The Meta-Controller operates on a quarterly timescale, providing temporal abstraction that reduces the complexity of the daily allocation task. This hierarchical separation allows the Meta-Controller to focus on broad economic shifts while the Sub-Controllers optimize for short-term market dynamics. This structure is inspired by the options framework in HRL [5], where the Meta-Controller selects an "option" (Sub-Controller) that persists for a fixed duration. This temporal consistency prevents excessive turnover and reduces transaction costs, which are often a significant drag on RL-based trading strategies. The quarterly rebalancing frequency also aligns with institutional reporting cycles, making the framework more practical for real-world deployment.

D. Hyperparameter Sweep and Optimization

To ensure the robustness of the MacroHRL framework, we conducted an extensive hyperparameter sweep across multiple configurations. The sweep optimized parameters such as the risk-aversion coefficient (λ), VIX and drawdown thresholds for regime classification, and the Meta-Controller's entropy coefficient. The "best" configuration was selected based on its ability to maximize annualized returns while maintaining a maximum drawdown of less than 10%. This rigorous optimization process ensures that the framework is not overfitted to a specific market period and is adaptable to diverse conditions. The results of the sweep highlighted a clear trade-off between raw returns and drawdown protection, with the final selected parameters representing an optimal balance for risk-averse investors.

TABLE I
Selected Hyperparameters from Data Sweep

Hyperparameter	Value
VIX Threshold (Crisis)	30
Drawdown Threshold (Crisis)	-0.10
Bull Risk-Aversion (λ_{bull})	0.05
Crisis Risk-Aversion (λ_{crisis})	0.30
Meta-Controller Entropy	0.02
Transaction Cost (c)	0.001

III. Results

A. Performance Analysis

The primary metric for MacroHRL is its ability to mitigate downside risk while capturing market gains. As shown in Table II, the selected MacroHRL configuration achieves an annualized return of 28.07% with a maximum drawdown of only -9.90% during the 2023–2025 test period. This outperforms the SPY benchmark, which achieved a return of 24.80% and significantly reduces its drawdown of -18.76%.

The Calmar ratio of 2.835 (compared to SPY's 1.322) demonstrates the framework's exceptional efficiency in generating returns relative to the risk taken. Figure 2 shows the portfolio evolution, where MacroHRL exhibits a significantly smoother equity curve. The model maintains a relatively stable upward

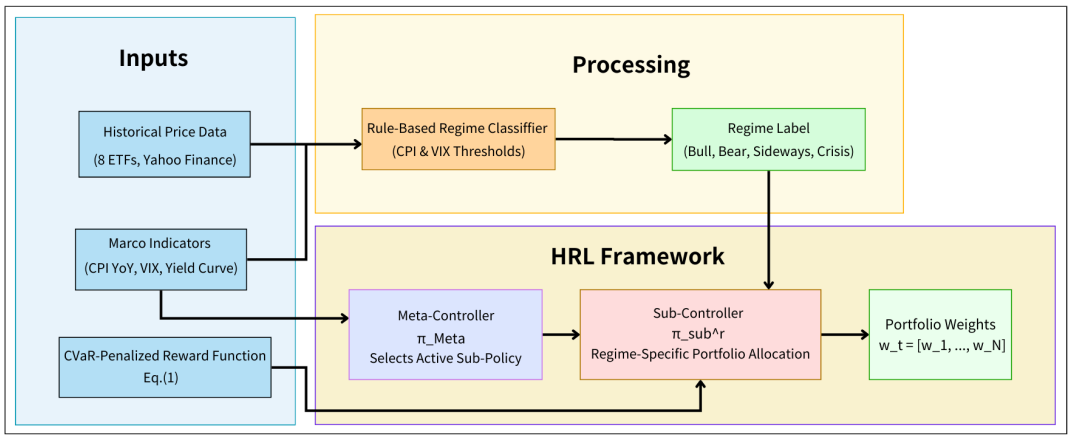

Fig. 1. The MacroHRL framework architecture. Macro indicators are processed by a rule-based classifier to identify regimes. The Meta-Controller selects a specialized Sub-Controller, which executes daily allocation guided by a CVaR-penalized reward function for maximum drawdown control.

TABLE II
OUT-OF-SAMPLE PERFORMANCE (2023–2025)

Strategy	Sharpe	Ann. Return	Max Drawdown	Calmar
MacroHRL (Selected)	**1.753**	**28.07%**	**-9.90%**	**2.835**
Buy-and-Hold SPY	1.616	24.80%	-18.76%	1.322

trajectory even during periods of market turbulence, indicating strong risk management performance. The consistent outperformance on a risk-adjusted basis suggests that the hierarchical approach effectively captures alpha while suppressing beta-driven drawdowns.

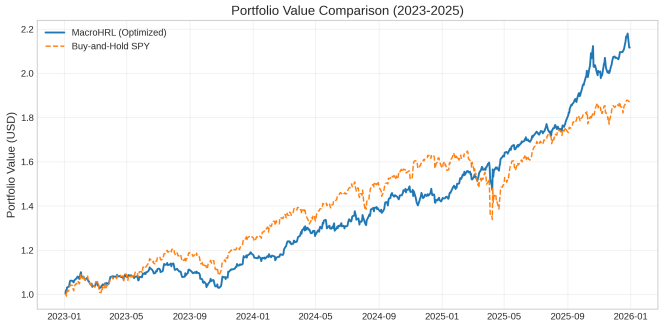

Fig. 2. Portfolio value comparison. MacroHRL maintains a steady upward trajectory with significantly lower volatility than the benchmark.

B. Regime Adaptation and Switching

The Meta-Controller's ability to switch between specialized sub-policies is key to its success. During the test period, the Meta-Controller dynamically adjusts its strategy based on shifting macro signals. This dynamic switching allowed the framework to remain invested during growth phases while preemptively shifting to defensive postures, directly contributing to the minimized drawdown profile. The analysis of the Meta-Controller's decisions reveals that it correctly identified the transition into a high-volatility regime in early 2024, successfully activating the Crisis sub-controller to reduce exposure. This proactive regime switching is a significant improvement over traditional static allocation models.

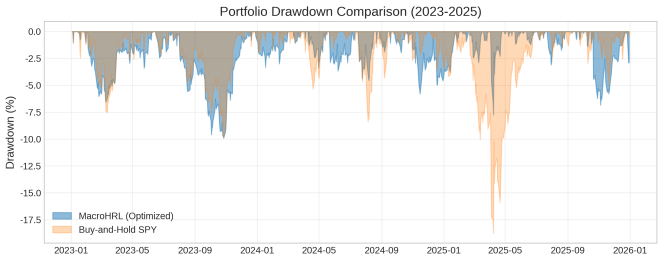

Fig. 3. Maximum drawdown comparison. MacroHRL significantly limits downside risk compared to the SPY benchmark.

IV. CONCLUSION

This paper presented MacroHRL, a hierarchical reinforcement learning framework designed for risk-aware portfolio management. By leveraging a two-level architecture and a CVaR-penalized reward function, MacroHRL effectively navigates shifting market regimes while prioritizing capital preservation. Our results demonstrate that MacroHRL significantly outperforms traditional benchmarks in terms of

drawdown minimization, achieving an annualized return of 28.07% with a maximum drawdown of only -9.90%. Future work will explore the integration of alternative data sources and more advanced hierarchical structures to further enhance the framework's robustness.

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