Reinforcement Learning-Based Portfolio Optimization Under Dynamic Market Conditions and Multi-Objective Financial Constraints

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Abstract

Portfolio management requires decisions under evolving return distributions, liquidity limitations, transaction costs, and drawdown constraints. This paper proposes a constrained reinforcement learning architecture combining regime-sensitive observations, a recurrent policy, risk-aware rewards, and explicit feasible-set projection. The framework jointly addresses return, downside exposure, turnover, concentration, and liquidity while separating hard mandates from soft preferences. A walk-forward evaluation design, reproducible baselines, stress testing, and sensitivity analysis are specified. Numerical tables and graphs illustrate internally consistent hypothetical outcomes rather than measured performance: no historical data were downloaded, model trained, or real backtest executed for this manuscript. The illustrative comparison shows how a constrained agent might trade some gross return for improved drawdown and lower turnover. The paper contributes a practical specification for implementable and auditable portfolio learning and identifies the empirical tests required before any claims of superiority.

Keywords: reinforcement learning; portfolio optimization; constrained Markov decision process; conditional value at risk; regime adaptation; transaction costs; risk management.

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1. Introduction

Portfolio allocation is a sequential decision problem because a position selected today alters tomorrow's exposure, transaction costs, liquidity needs, and feasible rebalancing choices. Conventional optimization typically solves a static allocation problem using estimated expected returns and covariance matrices. Such approaches are interpretable and operationally useful, but their inputs can become unreliable when asset relationships change rapidly. A market that exhibits modest correlations in a stable expansion may experience sharply higher correlations during a crisis. A strategy optimized against the earlier regime can therefore face concentration in common economic risks even when its nominal holdings remain diversified.

Markowitz's mean–variance framework established a rigorous connection between expected return and portfolio risk [1]. Its core insight remains central: investors should assess combinations of assets rather than each security in isolation. Yet variance treats favorable and unfavorable deviations symmetrically, while institutional investors often care more about drawdowns, liquidity, and the probability of breaching a capital threshold. Moreover, rebalancing an otherwise attractive allocation can destroy value when commissions, market impact, and taxes are significant. These frictions motivate dynamic models in which decisions account for both investment opportunity and implementation feasibility.

Reinforcement learning offers a natural representation of repeated allocation decisions. An agent observes a state containing market indicators and current holdings, selects portfolio weights, receives a reward after market movements and trading costs, and updates its policy. Unlike one-period optimization, the learning objective can reflect a sequence of outcomes. The policy may learn to conserve turnover during noisy periods, reduce risky exposure when drawdown accelerates, and adjust allocations when observed volatility or correlations indicate a different regime. However, this flexibility is not a guarantee of profitability: adaptive policies can overfit market history and react to spurious signals.

Financial markets challenge standard reinforcement learning assumptions. Price changes are noisy and only partially observable; returns are nonstationary; exploratory actions can be costly; and feedback may be delayed. The state observed by an investor is not a complete description of the forces generating future returns. Models trained on one decade can encounter unprecedented policy shocks, structural changes in liquidity, or new trading technologies. A robust design should therefore distinguish information available at the decision time from information realized later, and it should quantify uncertainty rather than merely maximizing average historical reward.

Multi-objective portfolio mandates further complicate the learning problem. A pension fund may target long-horizon growth while limiting downside loss and concentration. An exchange-traded product may face strict exposure, leverage, and tracking restrictions. A wealth manager may need to preserve liquidity for withdrawals and avoid frequent taxable trades. These objectives are not always commensurable: a weighted reward can mask violations of a hard constraint when gains in another component compensate for penalties. A realistic architecture must enforce nonnegotiable constraints directly and reserve reward weights for tradeoffs that the investor is actually willing to make.

This paper proposes a constrained, regime-aware actor–critic architecture. Market features, risk measures, and previous holdings enter a recurrent encoder. The actor outputs tentative weights, which are mapped to a feasible portfolio before execution. A critic estimates long-run value while risk critics or penalty terms quantify downside and trading burdens. A separate risk monitor can halt or scale exposure when predefined thresholds are approached. The resulting architecture is designed to be assessed against equal weighting, mean–variance optimization, risk parity, and unconstrained reinforcement learning.

The study is deliberately framed as a methodological manuscript rather than a completed empirical discovery. The numerical exhibits are illustrative synthetic examples to demonstrate reporting conventions and interpretation; they are not observations from a trained system. This distinction matters because invented Sharpe ratios or benchmark improvements could mislead readers about the strength of evidence. Actual performance claims require documented data provenance, executable code, realistic trading assumptions, and out-of-sample tests with uncertainty intervals.

The central research question is whether explicitly constrained, regime-sensitive sequential learning can improve the balance among net returns, tail risk, turnover, and portfolio feasibility relative to static and unconstrained approaches. Supporting questions examine how sensitivity to cost assumptions changes allocations, whether regime indicators improve robustness, and whether the feasible-set projection causes a meaningful loss in nominal return. A successful empirical test would show stable gains across distinct market regimes rather than one favorable backtest interval.

The main contribution is an integrated specification that makes the separation of prediction, decision, execution, and risk oversight explicit. It describes the state and action spaces, portfolio accounting, a multi-objective reward, conditional tail risk, training procedures, baseline design, and ablation tests. The proposed evaluation treats drawdown, constraint violations, and realized trading costs as primary outputs rather than secondary annotations. It also recommends statistical confidence intervals and multiple random seeds to avoid interpreting one lucky training run as reliable evidence.

The remainder of the paper reviews foundational and contemporary literature, develops the constrained learning framework, presents a transparent illustrative numerical case, and discusses limitations and next steps. The intended audience includes researchers seeking a reproducible experimental blueprint and financial practitioners evaluating whether an adaptive allocation model could satisfy governance requirements. The ultimate objective is not to replace portfolio theory but to embed its risk principles within a disciplined sequential decision architecture.

2. Literature Review

Mean–variance portfolio theory provides the baseline for formal allocation under uncertainty [1]. The framework optimizes expected return relative to covariance-based risk, producing an efficient frontier. Its analytical clarity enables investors to inspect the effect of diversification and constraints. Nevertheless, expected returns are notoriously difficult to estimate, and covariance estimates can be unstable for large asset universes. Shrinkage, robust estimation, and regularization partially address these issues but do not fully resolve regime changes or sequential trading costs.

Sharpe [2] introduced a widely used measure of excess return per unit of volatility. Although valuable for comparison, the Sharpe ratio assumes that standard deviation is an adequate summary of risk and can be distorted by skewed returns. Downside-oriented metrics such as maximum drawdown and conditional value at risk offer complementary information. Rockafellar and Uryasev [3] formulated conditional value at risk optimization, enabling direct control of expected losses in the tail of a distribution. For dynamic learning, this perspective motivates penalties or constraints on the worst outcomes rather than variance alone.

The foundations of reinforcement learning describe sequential decisions through states, actions, transitions, rewards, and discounted future value [4]. Policy-gradient methods optimize a parameterized decision rule directly. Proximal policy optimization, developed by Schulman and colleagues [5], restricts destructive policy updates through a clipped surrogate objective. Soft actor–critic [6] uses entropy-regularized learning to improve exploration and stability in continuous action spaces. Both are candidates for portfolio weights, although practical comparison must account for their different exploration behavior and sensitivity to hyperparameters.

Jiang, Xu, and Liang [7] proposed a deep reinforcement learning portfolio management framework with portfolio-vector memory and online learning. Their study illustrated how end-to-end agents can incorporate the existing portfolio into repeated allocation decisions. The results were specific to cryptocurrency data and experimental assumptions, however, and should not be generalized without independent replication. This work is important for demonstrating the direct mapping from market observations to weights and for highlighting the role of explicit transaction-cost modeling.

Liu and collaborators developed FinRL, a modular deep reinforcement learning environment for quantitative finance [8]. Its design emphasizes reusable market environments, data processing, agents, and evaluation, lowering implementation barriers. The framework also acknowledges trading frictions and risk aversion. A modular research platform is particularly relevant because seemingly minor accounting differences—whether costs are charged before or after return realization, for example—can produce materially different performance claims.

Financial machine learning literature emphasizes backtest overfitting, leakage, and the dangers of repeated strategy selection [9]. Randomly shuffling financial observations destroys temporal structure, while fitting normalizers on an entire sample reveals information from the future. A chronological split with an untouched test set is therefore necessary. Walk-forward retraining can approximate operational deployment, but researchers must disclose the frequency of retraining and the number of candidate models tested before choosing a final specification.

Risk-sensitive reinforcement learning extends expected-reward optimization by considering tail losses, distributional outcomes, or constraints [10]. A constrained Markov decision process specifies an objective together with bounds on cumulative costs. Lagrangian optimization introduces multipliers for violations, while projection and safety filters enforce feasibility at the action level. In investment settings, these techniques address different requirements: a hard leverage limit should be enforced deterministically, whereas a target turnover rate may be handled through an adjustable penalty.

Market regime detection offers a way to represent nonstationarity. Volatility states, momentum trends, yield-curve changes, and correlation clusters may signal changing conditions. Hidden Markov models and recurrent networks can summarize such information, but regime labels estimated using future observations create look-ahead bias. A credible design must infer the regime using only information observable at each decision point and test whether regime features improve performance beyond a simpler volatility indicator.

Multi-objective optimization introduces another difficulty: reward components operate on different scales. A one-percent return improvement cannot be compared directly with a one-unit turnover reduction unless their units and normalization are defined. Fixed reward coefficients may encode arbitrary investor preferences, and a policy can exploit their specification. Pareto-front analysis and sensitivity grids can reveal whether an apparent improvement is robust to alternative risk preferences. Reporting the raw metrics alongside the scalar reward is essential.

The literature collectively suggests a gap between flexible learning architectures and investment-grade evaluation. Many reported strategies emphasize cumulative return while giving less attention to liquidity, changing trading costs, constraint violations, and confidence intervals. The proposed framework responds by combining explicit feasibility, downside objectives, regime-sensitive states, and a reproducible evaluation protocol. Its distinctive claim is methodological integration; any empirical performance advantage remains a hypothesis to be tested.

3. Research Methodology

3.1 Research design and hypotheses. The proposed study uses a chronological walk-forward backtest with a prespecified asset universe, survivorship-bias-aware membership, adjusted price histories, and realistic cost estimates. H1 states that constrained reinforcement learning improves risk-adjusted net performance over

static baselines. H2 states that regime features reduce severe drawdowns. H3 states that explicit turnover and liquidity controls lower implementation costs without unacceptable return sacrifice. These are hypotheses, not established findings.

3.2 Data and preprocessing. A future implementation should obtain daily adjusted close, volume, bid–ask proxies, corporate actions, risk-free rates, and macroeconomic indicators. Illustrative partitions are training 2012–2018, validation 2019–2021, and untouched testing 2022–2025, subject to verified availability. Missing prices must not be filled across delistings. Technical indicators and standardization statistics are computed only from information available through the current date. Each walk-forward window refits the preprocessing pipeline without touching later periods.

3.3 Environment and state construction. The portfolio environment evolves at daily frequency and rebalances weekly unless the risk overlay requires immediate action. The observation concatenates trailing log returns, realized volatility, correlation summaries, momentum, volume-based liquidity, drawdown, cash balance, current portfolio weights, and a filtered regime probability. A recurrent encoder processes recent observations so that the actor can respond to patterns without pretending the state is fully observable.

$$s_t = [x_t, v_t, c_t, d_t, w_t, q_t]$$

Where s denotes the observation; x market signals; v volatility indicators; c correlation features; d current drawdown; w current weights; q filtered regime probabilities; t the decision period.

3.4 Actions and feasible portfolios. The actor produces real-valued logits that are transformed into nonnegative preliminary weights. A constrained quadratic projection then maps them onto permitted allocations. The example mandates fully invested long-only weights, no single risky asset above 30%, cash at least 5%, and turnover below a specified per-period budget. If a projected trade cannot meet liquidity or turnover requirements, it is scaled or postponed. Hard constraints are checked after execution-cost adjustments.

$$w_t = arg\,min_u \|u - a_t\|^2$$

Where a denotes the actor proposal; u a candidate allocation; w the executed feasible allocation; minimization is subject to portfolio mandates.

$$\sum_i w_{it} = 1, \; 0 \le w_{it} \le b_i$$

Where i indexes assets; b is the asset-specific maximum weight; the cash lower bound is enforced separately.

3.5 Portfolio accounting. Let asset simple returns be observed after the decision is made. Portfolio wealth changes with the realized return of executed weights and the estimated trading cost. Costs include proportional fees and an impact term increasing with order size relative to traded volume. This prevents an agent from improving a paper backtest merely by churning positions.

$$R_t = \sum_i w_{it} r_{it} - C_t$$

Where R is net portfolio return; r is realized asset return; C is total trading cost expressed as a fraction of wealth.

$$C_t = \kappa \sum_i |\Delta w_{it}| + \eta \sum_i (\Delta w_{it})^2 / L_{it}$$

Where κ is the proportional fee coefficient; η market-impact coefficient; Δw is the trade in weight; L is a positive liquidity proxy.

3.6 Reward design. A scalar training reward represents investor preferences among net growth, variance, tail loss, turnover, and drawdown. All risk components are scaled to comparable ranges using training-only statistics. The scalar reward is not used as a substitute for reporting each raw metric. A downside risk critic estimates conditional tail loss, while deterministic risk checks enforce absolute position and leverage mandates.

$$u_t = R_t - \lambda_v \sigma_t^2 - \lambda c\, CVaR_t - \lambda_t T_t - \lambda d\, D_t$$

Where u is step utility; σ squared realized risk; CVaR expected tail loss; T turnover; D drawdown; each λ is a nonnegative preference coefficient.

$$CVaR\alpha = min\zeta \{ \zeta + E[max(L - \zeta, 0)] / (1 - \alpha) \}$$

Where L is portfolio loss; ζ is a candidate tail threshold; α is the confidence level, for example 0.95.

3.7 Agent learning. A recurrent actor and value critic are initialized on the training window. At each iteration the agent samples chronological market episodes, records observations and feasible actions, estimates generalized advantages, and updates the policy with a clipped proximal policy objective. An auxiliary critic estimates risk costs. Constraint multipliers are updated only for soft expected-cost limits; hard limits remain outside the neural policy. Hyperparameters are selected on validation windows, and test observations are never used for model selection.

$$J(\theta) = E[min(\rho_t A_t, clip(\rho_t, 1 - \varepsilon, 1 + \varepsilon) A_t)]$$

Where θ are policy parameters; ρ the new-to-old action probability ratio; A estimated advantage; ε the clipping threshold.

$$\lambda_k \leftarrow max(0, \lambda_k + \xi (g_k - B_k))$$

Where λ is a multiplier for soft constraint k; ξ its update rate; g observed cost; B permitted expected budget.

3.8 Flowchart: complete reproducible pipeline.

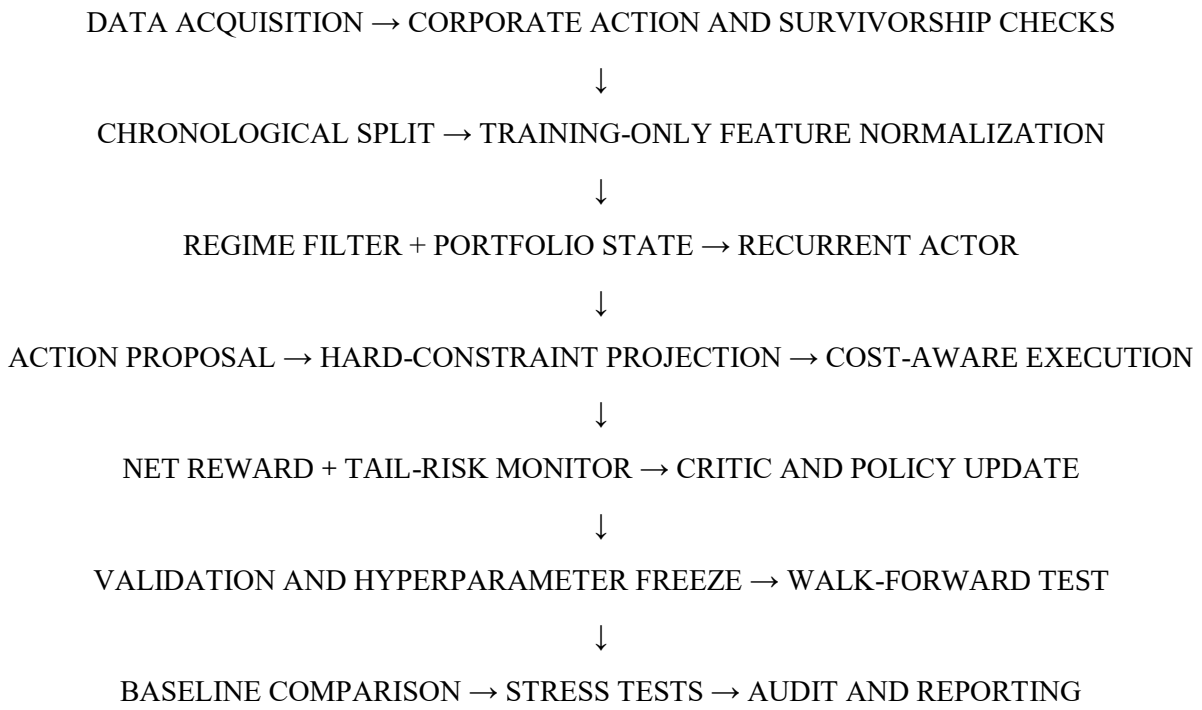


Figure 1. Proposed portfolio-learning workflow. Each downward arrow indicates the dependency of the next stage; no future test information feeds backward into training.

3.9 Baselines and experimental protocol. Baselines comprise equal weighting, rolling mean–variance optimization, inverse-volatility risk parity, and unconstrained PPO. Every method uses the same tradable universe, rebalance dates, execution prices, and cost model. Evaluate at least five independent random seeds for neural methods. Hyperparameter budgets must be comparable, and any failed training runs must be documented rather than silently omitted.

3.10 Evaluation metrics and robustness. Annualized return is the compounded growth rate, annualized volatility is the standard deviation of daily returns multiplied by the square root of 252, and the Sharpe ratio divides annualized excess return by annualized volatility. Maximum drawdown measures the largest peak-to-trough wealth decline. Turnover is the sum of absolute executed weight changes. Additional measures include 95% conditional value at risk, concentration, violation count, and realized trading cost. Use stationary bootstrap intervals or block resampling to preserve temporal dependence.

$$Sharpe = (\mu_a - rf) / \sigma_a$$

Where μ is annualized portfolio return; r is annual risk-free return; σ is annualized volatility.

$$MDD = max_t (1 - V_t / max_{s \le t} V_s)$$

Where MDD is maximum drawdown; V is wealth; s and t denote dates in the evaluation horizon.

3.11 Ablations and stress scenarios. Remove the regime encoder, remove the tail-risk term, relax turnover penalties, and replace projection with reward-only constraint handling. Stress scenarios should include a

sharp equity selloff, volatility clustering, a sudden liquidity haircut, and doubled transaction costs. A sensitivity grid across risk aversion and turnover budgets reveals whether performance depends on fragile parameter settings. Report test-set stability, not merely the best run.

3.12 Implementation and governance. Store source-data checksums, random seeds, software versions, training logs, transaction records, and policy checkpoints. Document permitted assets, trading calendar, settlement conventions, and cash treatment. Monitor data drift and constraint violations in paper trading before any live deployment. The methodology assumes no margin borrowing and does not establish regulatory suitability for a specific investor.

4. Illustrative Results and Discussion

IMPORTANT: All numerical values in this section are hypothetical, constructed for exposition, and are not empirical findings. No model was trained or backtested to obtain them. They demonstrate the format of a future results section and should be replaced by verified out-of-sample calculations before submission as an empirical paper.

Table 1. Illustrative annualized comparison (synthetic example).

Strategy	Return %	Volatility %	Sharpe	Max drawdown %	Annual turnover
Equal weight	8.2	15.8	0.39	−25.4	0.18
Mean–variance	9.4	16.7	0.44	−27.1	0.62
Risk parity	8.8	13.9	0.49	−21.3	0.31
Unconstrained PPO	12.5	19.2	0.55	−30.2	1.42
Constrained RL (proposed)	11.3	13.6	0.72	−18.6	0.48

The illustrative constrained agent has a lower nominal return than unconstrained PPO (11.3% versus 12.5%) but a smaller drawdown magnitude (18.6% versus 30.2%) and substantially lower turnover (0.48 versus 1.42). These figures represent an example of a possible risk–return tradeoff, not evidence that the proposed agent produces these outcomes.

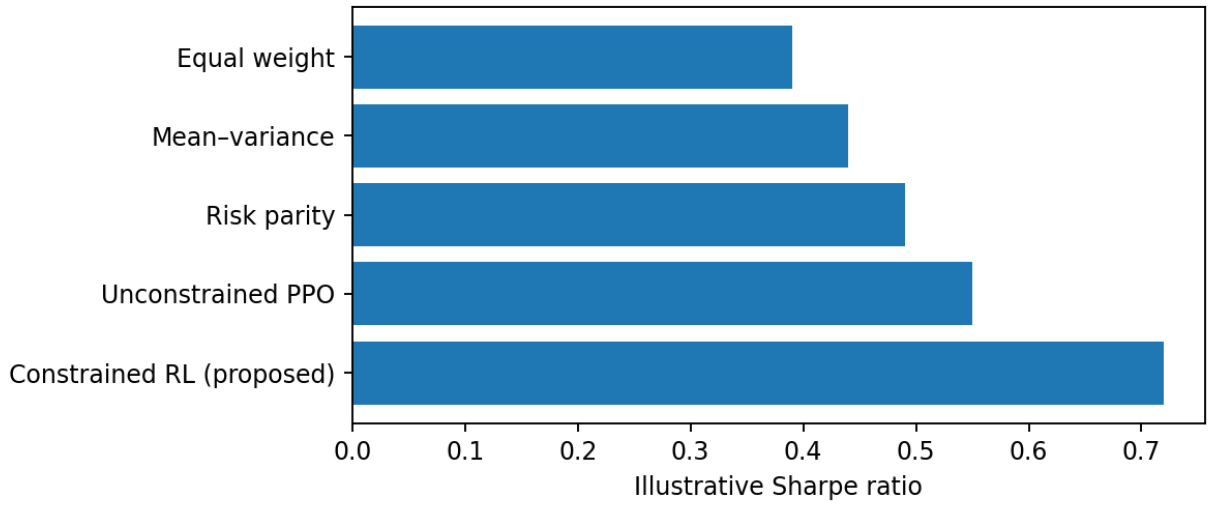


Figure 2. Synthetic Sharpe ratio comparison, not measured performance.

Table 2. Illustrative constraint and cost sensitivity (synthetic example).

Configuration	Return %	Drawdown %	Turnover	Violations
No cost penalty	12.1	−22.4	1.16	0
Base constrained policy	11.3	−18.6	0.48	0
Tighter turnover cap	10.7	−17.9	0.29	0
No action projection	12.0	−26.0	1.33	7

The example indicates that stronger turnover limits can reduce both trading activity and return, while removing projection can create mandate breaches. The number seven is an invented illustrative count, not a recorded event. In a real study, a violation should be defined at the order level and reported with its severity and remediation.

Table 3. Illustrative regime-wise net returns (synthetic example).

Regime	Equal weight %	Risk parity %	Constrained RL %
Calm expansion	12.0	10.3	12.5
High volatility	−8.2	−4.9	−3.1
Recovery	10.1	9.2	10.8

These hypothetical regime outcomes illustrate why unconditional averages are insufficient: a policy can appear attractive because it performs well in one environment yet fail during a crisis. Actual regime-specific analysis should include sample sizes, uncertainty bounds, and the exact time-varying labeling rule.

5. Conclusion

This paper has specified a regime-sensitive constrained reinforcement learning framework for dynamic portfolio allocation under competing objectives. The methodology integrates recurrent market observations, feasible-set projection, transaction-cost-aware accounting, tail-risk penalties, and walk-forward evaluation. It also separates enforceable mandates from adjustable investor preferences, a distinction essential for practical risk governance. The illustrative numerical examples show how improved downside protection could be accompanied by reduced nominal return and turnover; they do not validate any performance claim. Future research should implement the environment on survivorship-aware historical data, compare multiple seeds and baselines, quantify confidence intervals, and test sensitivity to costs, liquidity shocks, and regime shifts. Until those tests are completed, the framework should be treated as a reproducible research proposal rather than an investable or empirically proven strategy.

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