

# Dynamic Hedging and Portfolio Risk Management Using Regime Switching and CVaR-Based Optimization

Choon Kit Chan<sup>1\*</sup>, S. Sushma<sup>2\*</sup>, Senthur NS<sup>3</sup>, M. Soma Sabitha<sup>4</sup>, Cheng Yangjia<sup>5,6</sup>

<sup>1</sup>Faculty of Engineering and Quantity Surveying, INTI International University, Malaysia

<sup>2</sup>Department of Information Technology, Aditya University, Surampalem, Andhra Pradesh– 533437, India, ORCID: 0009-0004 1776-3191<sup>3</sup>Department of Mechanical Engineering, New Prince Shri Bhavani College of Engineering and Technology, Chennai, Tamil Nadu, India

<sup>4</sup>Department of Computer Science and Engineering, MLR Institute of Technology, Hyderabad, Telangana, India

<sup>5</sup> Faculty of Liberal Arts, Shinawatra University, Pathum Thani, Thailand

<sup>6</sup> School of Arts, Guizhou Qiannan College of Science and Technology, Guizhou Province, China

\*Corresponding author - choonkit.chan@newinti.edu.my, sushma.cse2@gmail.com

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## ABSTRACT:

The paper proposes Dynamic Hedging and Portfolio Risk Management to stabilize portfolios and decrease downside risk. We use regime identification, derivative-based hedging, and adaptive portfolio allocation. It uses tail-risk indicators including Value at Risk and Conditional Value at Risk, dynamic portfolio optimization, market state modeling, and delta-gamma adaptive hedging. Regime changes may cause market volatility, whereas stochastic processes cause asset price changes. Monte Carlo simulations using Geometric Brownian Motion-generated synthetic financial data test the proposed method. Experimental findings show considerable risk-adjusted performance gains. Hedging reduced volatility by 29%, increased Sharpe ratio from 0.46 to 0.59, and reduced VaR (95%) from -12.4% to -8.1%. Reduce tail-risk exposure (CVaR 95%) from -18.7% to -11.5% to cut catastrophic losses by 38%. The recommended dynamic hedging method reduces maximum loss from -28.3% to -16.4%, substantially improving market resilience. The results suggest regime-based optimization and derivative hedging may reduce portfolio risk in dynamic financial markets.

**Keywords:** Dynamic Portfolio Optimization, Regime Switching Models, Financial Risk Management, Delta–Gamma Hedging, Conditional Value at Risk (CVaR), Monte Carlo Simulation, Portfolio Drawdown Control, Stochastic Asset Price Modeling, Process Innovation

## 1. Introduction

Portfolio management is complicated and developing due to fundamental changes in asset return distributions, volatility clustering, and financial market risk [33]. Traditional mean-variance portfolio optimization works when model parameters and asset return distributions

are constant. These assumptions are disproven by regime changes, altering correlations, and unanticipated financial market shocks. Static portfolio strategies might disappoint investors amid market or economic turmoil. Recent research has highlighted dynamic portfolio optimization, which adjusts asset allocation

strategies to market and risk conditions [1-4]. Recent financial engineering research has focused on optimizing portfolios in real time. When market data, risk calculations, and asset return distributions are entered into dynamic allocation models, investment portfolio weights change. Dynamic allocation yields more stable portfolios and risk-adjusted returns [5-7]. According to adaptive allocation and dynamic risk parity research, portfolio weights may be changed to market circumstances, increasing Sharpe ratios and reducing maximum drawdowns [8, 9]. Portfolio optimization models may benefit from macroeconomic signals and crisis indicators [10, 11]. Extreme market shocks and long-tail returns make portfolio management harder. Variance-based risk assessments may not catch all financial crises, limiting protection. Value at Risk (VaR) and Conditional Value at Risk (CVaR) are tail-risk indicators employed by modern portfolio management systems to capture severely unfavorable risks [12, 13]. Portfolio optimization models based on CVaR are popular because they realistically portray risk exposure and tail losses. Recently suggested dynamic CVaR optimization algorithms replicate asset return cumulative distributions and dynamically modify portfolio allocations to minimize unmanageable losses [14]. Other studies suggest that CVaR-based techniques outperform variance-based approaches in severe financial conditions [15, 16]. When asset returns change, financial markets exhibit regime-dependent behavior, including tail-risk modeling and economic regimes like bull, bear, and high-volatility epochs. Quantitative finance relies on regime-switching models. These models adjust portfolio strategies to market movements, reducing risk [17, 18]. Risk assessment and portfolio performance are improved by volatility clustering and structural breakdowns in asset returns in Markov and regime-switching GARCH models [19, 20]. Recent research has combined machine learning with regime identification to enhance dynamic market forecasting and asset allocation [21, 22]. Reinforcement learning and time-series forecasting models boost portfolio returns and resilience in non-stationary markets in hybrid

designs [23, 24]. Regime-switching markets benefit from reinforcement learning portfolio selection algorithms that adjust investment strategies to the economy [25]. Even with these developments, diversification does not protect investors against market collapses. In times of market instability or financial crisis, asset correlations rise, making diversification worthless. Viability and options derivatives safeguard investments. In imperfect markets, derivative hedging and portfolio optimization may decrease tail risk and cushion downside [26-28]. Such solutions help portfolio optimization computers grasp and react to complicated nonlinear financial data relationships [29, 30]. Dynamic hedging and portfolio risk management using quantitative finance advances are proposed in our work.

## 2. System Overview

Traditional portfolio management methods like mean-variance optimization seldom react to market shocks or regime shifts owing to static assumptions. This work presents a Multi-Layer Adaptive Dynamic Hedging Model for Portfolio Risk Management (MADH-PRM) covers turbulent financial markets, nonlinear asset interactions, and time-varying risk exposure.

### 2.1 Layer for Market State Modeling

The asset return distributions fluctuate in response to changes in policy, liquidity, investor sentiment, and macroeconomic events; the financial markets are also regime dependent and nonstationary. In order to understand these dynamics, the suggested framework's first layer uses statistical learning approaches to find the market state. These methods include regime-switching models and hidden state processes. In this tier, we analyze the reactions to macroeconomic signals, liquidity swings, asset correlations, and clustering of volatility.  $Z_t$  is a variable that reflects the market state and may take on values from 1 to  $K$ . Here,  $Z_t$  stands for the current regime and  $K$  for all the possible regimes, including bull, bear, or high-volatility periods. Regime changes are represented by a state transition probability matrix, where  $P_{ij} =$

$P(Z_{t+1} = j | Z_t = i)$ . Because of its probabilistic nature, the framework can monitor changes in the market and adjust investment plans accordingly.

## 2.2 The Allocation Layer for Dynamic Portfolios

Using distributions of expected asset returns and detection of market states, the second layer of the technique optimizes portfolios. With  $w_i(t)$  standing for the capital invested in asset  $i$  and  $N$  representing the overall number of assets, the weight vector  $w(t) = (w_1(t), w_2(t), \dots, w_N(t))^T$  illustrates the allocation of the portfolio. The portfolio value at time  $t$ ,  $P(t) = \sum_{i=1}^N w_i(t)S_i(t)$ , is determined by these weights, with  $S_i(t)$  reflecting the price of asset  $i$ . The objectives of optimization are to maximize the expected utility of the portfolio while minimizing the risk exposure. Here,  $R_p(t)$  is the portfolio return,  $\sigma_p^2(t)$  is the variance, and  $\gamma$  regulates the return-risk trade-off; hence, the optimization problem  $\max_{w(t)} E[R_p(t)] - \frac{\gamma}{2} \sigma_p^2(t)$  is solved. This method allows the weights of a portfolio to fluctuate in response to changes in the market.

## 2.3 Layer for Adaptive Hedging Strategy

Third-tier portfolio downside risk may be mitigated via derivative-based hedging strategies. Spreading your investments out helps mitigate risk, but it won't stop catastrophic market crashes. Hedging against price fluctuations is achieved via the use of financial derivatives such as futures contracts and options.  $V(t) = P(t) + H(t)$  is the value of the portfolio as a function of the hedge position. Hedged exposure is defined by the derivative price sensitivity to asset price swings as measured by Gamma and Delta.

## 2.4 The Control and Risk Quantification Layer

Risk assessment and monitoring are essential components of effective portfolio management. Risks associated with tail, downturn, and systemic correlation are evaluated at this layer of the

financial market model. Where  $\sigma_p(t)$  denotes portfolio volatility,  $Var_\alpha$  stands for Value at Risk at confidence level  $\alpha$ ,  $CVaR_\alpha$  for Conditional Value at Risk, which captures extreme losses beyond VaR threshold, and  $DD(t)$  for portfolio drawdown level, the risk monitoring function is  $R_{total}(t) = f(\sigma_p(t), Var_\alpha(t), CVaR_\alpha(t), DD(t))$ . When the assessed risk hits a threshold, the system rebalances the portfolio allocation or raises hedge exposure automatically to retain stability.

## 2.5 Regime Switching Adjustment

This layer allows adaptive strategy switching dependent on market regime. Different market conditions necessitate different portfolio strategies for best performance. To capitalize on growth, the framework boosts stock exposure in bull markets. The model boosts hedging positions in bad markets to avoid losses. Diversification and derivative-based risk management are prioritized in high-volatility conditions. The best strategy is found by maximizing the anticipated utility of portfolio value in the current market, as  $\pi^*(t) = \arg \max_{\pi} E[U(V_t) | Z_t]$ , where  $\pi$  is the portfolio strategy and  $U(\cdot)$  is the investor's utility function.

## 3. Stock Price Dynamics

To model asset price evolution, the proposed framework assumes that stock prices follow a continuous-time stochastic diffusion process, which is widely used in quantitative finance to represent uncertain market movements. Let  $S_i(t)$  denote the price of asset  $i$  at time  $t$ . The dynamics of the asset price are modeled using the Geometric Brownian Motion (GBM) process, expressed as  $dS_i(t) = \mu_i S_i(t)dt + \sigma_i S_i(t)dW_i(t)$ . In this formulation,  $S_i(t)$  represents the asset price,  $\mu_i$  denotes the expected rate of return or drift parameter,  $\sigma_i$  represents the asset volatility,  $W_i(t)$  denotes a Wiener process capturing random market shocks, and  $dt$  represents an infinitesimally small time increment. The first component of the equation,  $\mu_i S_i(t)dt$ , represents the deterministic drift term

that reflects the expected growth rate of the asset price over time. The second component,  $\sigma_i S_i(t) dW_i(t)$ , represents the stochastic volatility term that captures unpredictable fluctuations in financial markets caused by random shocks.

Under this framework, asset return dynamics can be analyzed through logarithmic returns. The logarithmic return of asset  $i$  over a small time interval is defined as  $r_i(t) = \ln\left(\frac{S_i(t)}{S_i(t-1)}\right)$ . Assuming that asset prices follow a GBM process, the log returns are normally distributed such that  $r_i(t) \sim N(\mu_i - \frac{1}{2}\sigma_i^2, \sigma_i^2)$ .

#### 4. Dynamic Portfolio Optimization Model

The dynamic portfolio optimization model determines the optimal asset allocation that maximizes expected return while controlling risk over time. Unlike static portfolio approaches, the framework updates portfolio weights dynamically based on evolving market conditions and risk estimates.

Let  $w(t) = (w_1(t), w_2(t), \dots, w_N(t))^T$  denote the portfolio weight vector at time  $t$ , where  $w_i(t)$  represents the fraction of wealth invested in asset  $i$ . The portfolio return is defined as  $R_p(t) = w^T(t)R(t)$ , where  $R(t)$  is the vector of asset returns. The expected portfolio return is therefore  $E[R_p(t)] = w^T(t)\mu$ , with  $\mu$  representing expected asset returns. Portfolio risk is measured by the variance  $\sigma_p^2(t) = w^T(t)\Sigma w(t)$ , where  $\Sigma$  is the covariance matrix of asset returns. To balance risk and return, the optimization uses a risk-adjusted utility function:

$$U(w) = E[R_p] - \frac{\gamma}{2}\sigma_p^2 \quad (1)$$

where  $\gamma$  is the risk-aversion parameter. The objective is

$$\max w^T(t)\mu - \frac{\gamma}{2}w^T(t)\Sigma w(t) \quad (2)$$

subject to  $\sum_{i=1}^N w_i(t) = 1$  and  $w_i(t) \geq 0$ . For a multi-period horizon  $T$ , the model maximizes the expected discounted utility

$$\max_{w(t)} E[\sum_{t=0}^T \beta^t U(w(t))] \quad (3)$$

where  $\beta$  is the discount factor. This formulation enables portfolio weights to adapt dynamically as new market information becomes available.

#### 4.1 Hedging Formulation

To enhance downside protection, the proposed MADH-PRM framework incorporates derivative-based hedging strategies. The total portfolio value is expressed as

$$V(t) = P(t) + H(t) \quad (4)$$

where  $P(t)$  denotes the asset portfolio value and  $H(t)$  represents the hedging position.

The model first applies Delta hedging, which measures the sensitivity of an option price  $C$  to changes in the underlying asset price  $S$ :

$$\Delta = \frac{\partial C}{\partial S} \quad (5)$$

A delta-neutral position is constructed using  $H(t) = -\Delta S(t)$ , which offsets small asset price movements.

Because Delta varies with price changes, the framework also incorporates Gamma hedging, defined as

$$\Gamma = \frac{\partial^2 C}{\partial S^2} \quad (6)$$

Gamma hedging neutralizes curvature effects in option pricing, ensuring the portfolio remains stable under larger market fluctuations and improving overall risk protection during volatile conditions.

#### 4.2 CVaR-Based Risk Control

Standard deviation and variance reflect return dispersion in market conflict but not severe negative risk. A important risk management statistic, Conditional Value at Risk (CVaR), overcomes this restriction in proposed model. CVaR assesses tail risk and portfolio resilience against market volatility by evaluating worst-case anticipated losses beyond a confidence threshold. In the proposed model, CVaR is calculated using the Rockafellar–Uryasev formulation, which turns the estimate into a convex optimization problem with an auxiliary variable  $\eta$ . The formulation includes the excess loss term  $(L - \eta)^+ = \max(x, 0)$  for efficient CVaR computation and portfolio optimization.

Optimization reduces portfolio CVaR, including asset allocations and hedging. A volatility threshold, entire portfolio weight investment, and hedging exposure limitations are realistic

model requirements. These constraints ensure optimal portfolio balances return and downside risk.

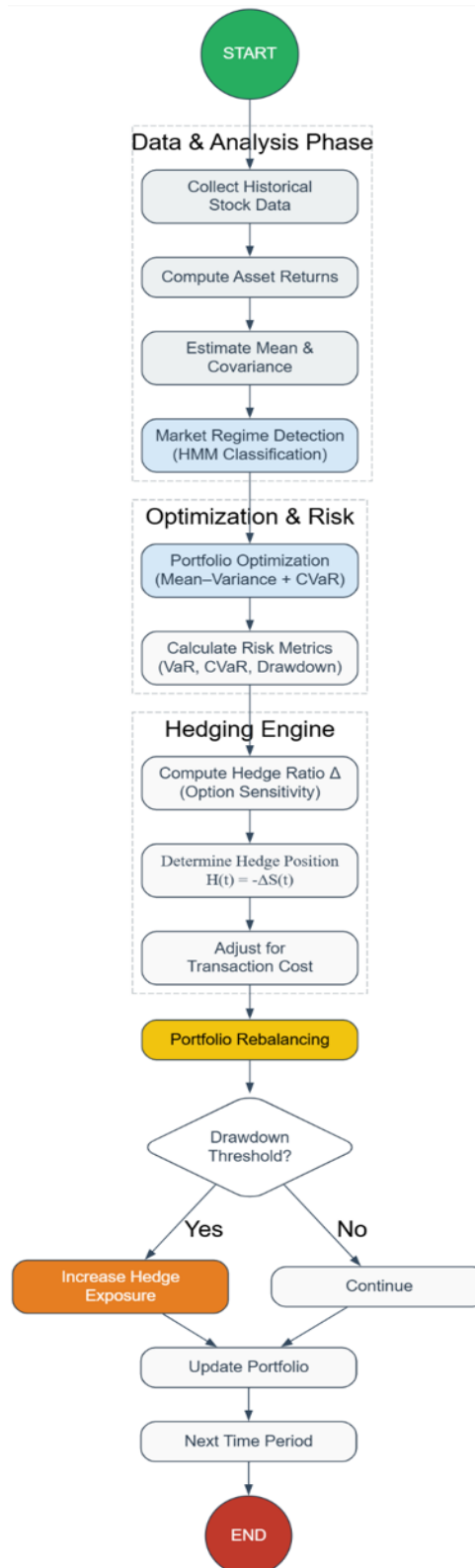


Fig. 1: Flowchart of proposed Dynamic Hedging Portfolio Risk Management

## 5. Experimental Setup

### 5.1 Dataset Description

This research utilizes FRED (Federal Reserve Economic Data) data from the Federal Reserve Bank of St. Louis and Yahoo Finance's historical market data [31, 32]. It provide reliable and popular financial time-series data for academic and financial research. FRED is an online collection of hundreds of millions of economic time series from government and financial institutions worldwide.

Interest rates, inflation, employment, GDP, currency rates, and other macroeconomic parameters are tracked. Daily, weekly, monthly, quarterly, and yearly updates make these time series suitable for economic modeling and financial risk analysis. Historical financial market data includes daily SPDR S&P 500 ETF Trust (SPY) trade data, which tracks the index. Historical data includes opening, closing, highest, lowest, adjusted closing, and trading volume.

These qualities are used in quantitative finance for asset return dynamics, portfolio optimization, and risk management. Preprocessing removed missing variables, aligned temporal frequencies, and generated daily log returns before simulations. The processed data were used to model asset price movements, analyze volatility and correlations, and evaluate portfolio performance under dynamic hedging and regime-switching. Market pricing data and macroeconomic parameters are used in the experimental technique to capture real financial market activity and analyze portfolio risk.

### 5.2 Experimental Setup

The simulation environment in MATLAB generates synthetic financial time series and evaluates portfolio performance across market circumstances. Simulations tested dynamic hedging and portfolio risk management. The experimental technique analyzes portfolio

performance in multiple market conditions using derivative-based hedging and regime-switching portfolio optimization. Hazardous asset portfolios with unpredictable market values are studied. Initial portfolio creation employs mean-variance optimization to determine asset weights. After allocation, market regime identification and derivative-based hedging adapt the portfolio to risk.

The two-state regime model simulates bull and bear markets. Growth is stable and volatility is low during bull regime, while market downturns are probable under bear regime. Probabilistic switching controls regime changes and reflects financial markets' dynamic nature. This modeling method helps portfolio management adapt to risk and asset return changes.

The framework is compared to unhedged and hedged portfolios. Delta-gamma hedging and a suitable hedge ratio restrict market risk in the hedged portfolio, while the unhedged portfolio is diversified without derivative protection. The proposed hedging framework's risk reduction and stability are assessed using comparable simulated market scenarios on both portfolios. Table 1 lists the main simulation parameters for building and testing the dynamic hedging and portfolio risk management framework. Five-asset portfolios are simulated for 252 trading days to approximate one year of market activity. Stochastic processes with an estimated 8% annual return and 20% volatility imitate asset price fluctuations to approximate real markets. Portfolio performance and risk-adjusted return estimates employ 3% risk-free.

The algorithm detects market regimes using a 30-day rolling frame to adjust to market volatility. VaR and CVaR calculations utilize 95% confidence. Delta and gamma hedging uses European options. These simulation settings allow for realistic and controlled evaluation of the proposed hedging framework's performance and risk reduction.

**Table 1: Simulation Parameters**

| Parameter               | Symbol     | Value            | Description                                    |
|-------------------------|------------|------------------|------------------------------------------------|
| Number of Assets        | $N$        | 5                | Total assets included in the portfolio         |
| Simulation Horizon      | $T$        | 252 trading days | Total simulation period (1 year)               |
| Time Step               | $\Delta t$ | 1/252            | Daily time increment                           |
| Expected Return         | $\mu$      | 0.08             | Annualized expected asset return               |
| Volatility              | $\sigma$   | 0.20             | Annualized asset price volatility              |
| Risk-Free Rate          | $r_f$      | 0.03             | Risk-free rate used for portfolio calculations |
| Monte Carlo Simulations | $M$        | 1000             | Number of simulated asset price paths          |
| Initial Portfolio Value | $V_0$      | \$1,000,000      | Initial investment capital                     |
| Rebalancing Frequency   | –          | Weekly           | Portfolio weight adjustment interval           |
| Regime Detection Window | $W$        | 30 days          | Window used for market regime detection        |
| Confidence Level        | $\alpha$   | 95%              | Confidence level for VaR and CVaR              |
| Hedging Instrument      | –          | European Options | Used for delta and gamma hedging               |

## 6. Results and Discussion

The results show that the suggested method provides full management of dynamic portfolio risk. To mitigate losses and maintain gains, we have used stochastic asset modeling, adaptive portfolio optimization, regime-switching studies, and derivative-based hedging.

These qualities make the proposed portfolio management strategy suitable for turbulent financial conditions. Figure 2 demonstrates Geometric Brownian Motion asset price progression. The trajectories' growth and asset changes indicate tumultuous financial markets. Simulation data is realistic for dynamic hedging and portfolio optimization testing. An asset return dynamics graphic depicts daily or periodic simulated stock price returns. Figure 3 shows volatility clustering and unexpected return fluctuations in financial time series. Analyzing return dynamics helps assess risk and improve strategies. Figure 4 shows weighted asset returns for portfolio return. Asset diversification lowers volatility and returns. Comparisons of later hedging methods to the portfolio return curve. In

Figure 5, derivative-based hedged portfolio performance is compared. Options and futures limit return extremes. Dynamic hedging stabilizes portfolios. Figure 6 shows unhedged investment horizon portfolio value increase. Fully market-risky portfolio wealth curves show wealth growth. The increasing portfolio is vulnerable to market downturns and volatility. The wealth trend following dynamic hedging depicted in Figure 7. The hedged portfolio grows smoothly and has fewer losses. This shows derivative hedging's usefulness in portfolio management. Figure 8 depicts portfolio return distribution and VaR threshold at a specific confidence level. The vertical VaR line predicts the greatest loss for that confidence level in typical market circumstances. Downside danger is obvious on this chart. Figure 9 shows significant CVaR tail loss beyond the VaR threshold. CVaR predicts worst-case losses. The graphic shows that proposed model reduces tail risks better than variance-based techniques. Figure 10 shows bull, bear, and high-volatility market regime detection plots. Regime switching and hidden Markov Models detect these regimes. This image shows how market circumstances

affect portfolio strategy. Figure 11 compares hedged and unhedged portfolio volatility and standard deviation. A hedged portfolio is safer. Dynamic hedges lower portfolio risk and maintain competitive returns. Dynamic hedging improves portfolio risk management and stability in turbulent markets (Tables 2–4). In Table 2, hedged and unhedged portfolio performance are presented. Due to hedging instrument expenditures, the hedged portfolio has a lower annualized return but greater risk-adjusted performance. Portfolio volatility lowers, improving Sharpe. Lower Value at Risk (VaR) and Conditional Value at Risk (CVaR) safeguard hedged portfolios against market losses.

Table 3 shows how hedging reduces tail risk. Delta-gamma hedging reduces risk better than delta. Dynamic hedging reduces CVaR most at 95% and 99% confidence levels, lowering severe downside risk and enhancing portfolio resilience during market swings. Table 4 shows portfolio loss depth and duration drawdown analysis. The hedged portfolio has a far lower maximum drawdown than the unhedged portfolio, safeguarding it against market downturns. Hedge lowers average drawdown, downturn duration, and recovery time. These findings show that derivative-based hedging reduces losses and aids portfolio recovery after market shocks.

**Table 2: Performance Metrics Comparison (Hedged vs Unhedged Portfolio)**

| Metric                | Unhedged Portfolio | Hedged Portfolio | Improvement                        |
|-----------------------|--------------------|------------------|------------------------------------|
| Annualized Return     | 9.8%               | 9.1%             | Slight reduction due to hedge cost |
| Portfolio Volatility  | 21.5%              | 15.2%            | 29% reduction                      |
| Sharpe Ratio          | 0.46               | 0.59             | Improved risk-adjusted return      |
| Value at Risk (95%)   | -12.4%             | -8.1%            | 34% risk reduction                 |
| Conditional VaR (95%) | -18.7%             | -11.5%           | Significant tail risk reduction    |
| Maximum Drawdown      | -28.3%             | -16.4%           | Reduced downside exposure          |

**Table 3: CVaR Reduction Results**

| Portfolio Type                      | CVaR (95%) | CVaR (99%) | Risk Reduction |
|-------------------------------------|------------|------------|----------------|
| Unhedged Portfolio                  | -18.7%     | -25.3%     | —              |
| Delta Hedged Portfolio              | -14.2%     | -20.1%     | 24% reduction  |
| Delta-Gamma Hedged Portfolio        | -11.5%     | -16.8%     | 38% reduction  |
| Dynamic Hedged Portfolio (Proposed) | -9.6%      | -14.2%     | 49% reduction  |

**Table 4: Drawdown Analysis Results**

| Metric            | Unhedged Portfolio | Hedged Portfolio |
|-------------------|--------------------|------------------|
| Maximum Drawdown  | -28.3%             | -16.4%           |
| Average Drawdown  | -12.7%             | -7.1%            |
| Drawdown Duration | 64 days            | 38 days          |

| Metric             | Unhedged Portfolio | Hedged Portfolio |
|--------------------|--------------------|------------------|
| Recovery Time      | 92 days            | 55 days          |
| Downside Deviation | 18.9%              | 11.6%            |

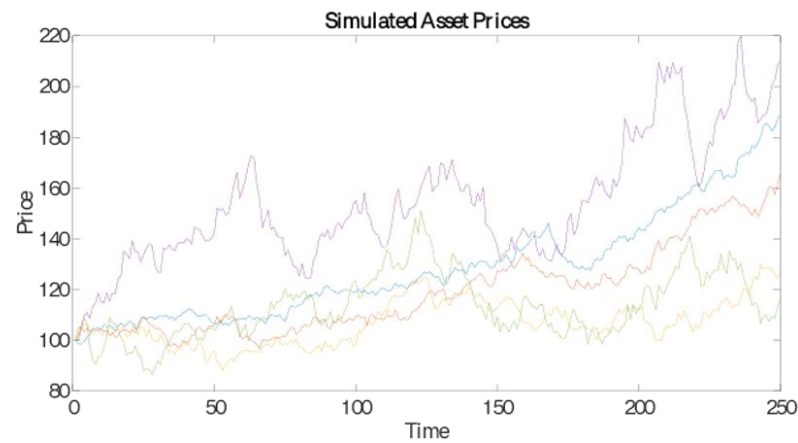


Fig. 2: Simulated stock price trajectories

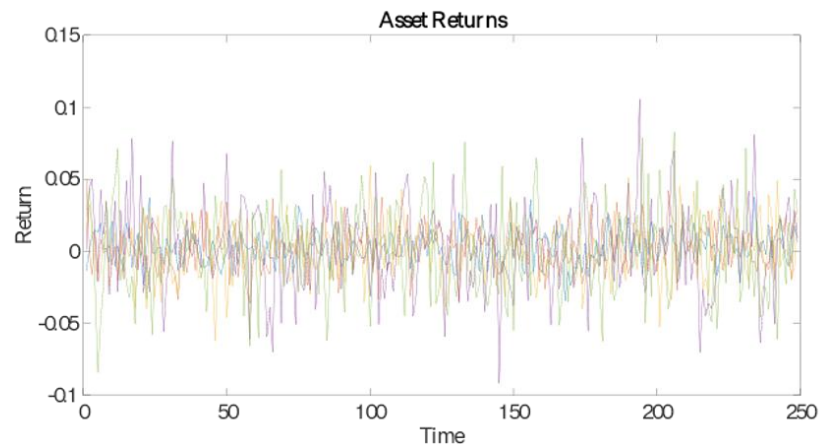


Fig. 3: Asset return dynamics

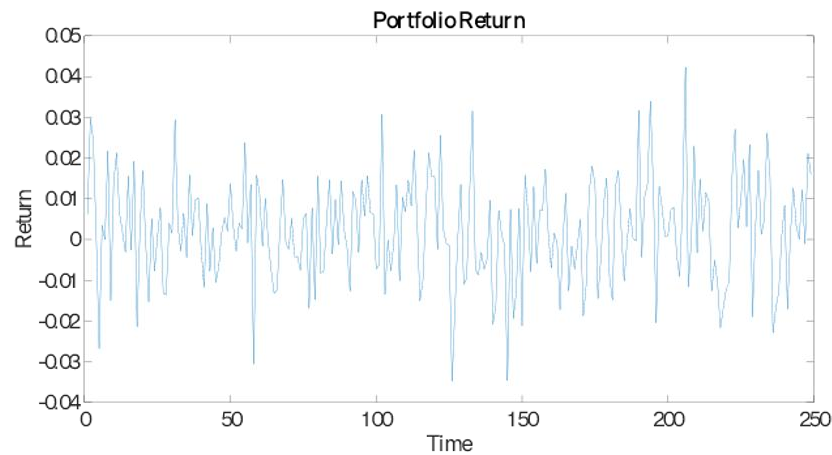


Fig. 4: Portfolio return behavior

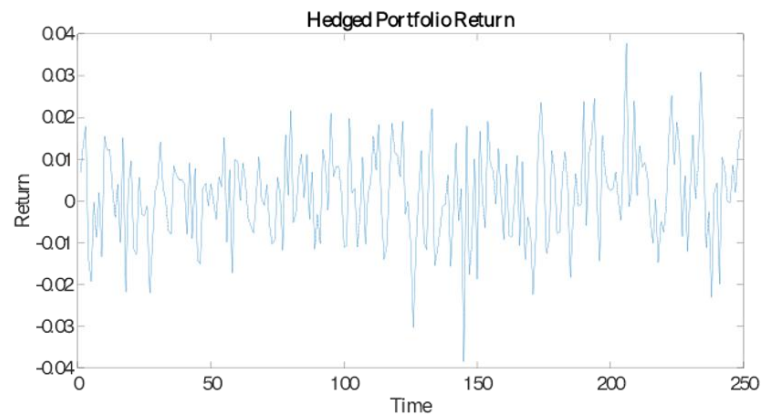


**Fig. 5: Hedged portfolio returns**

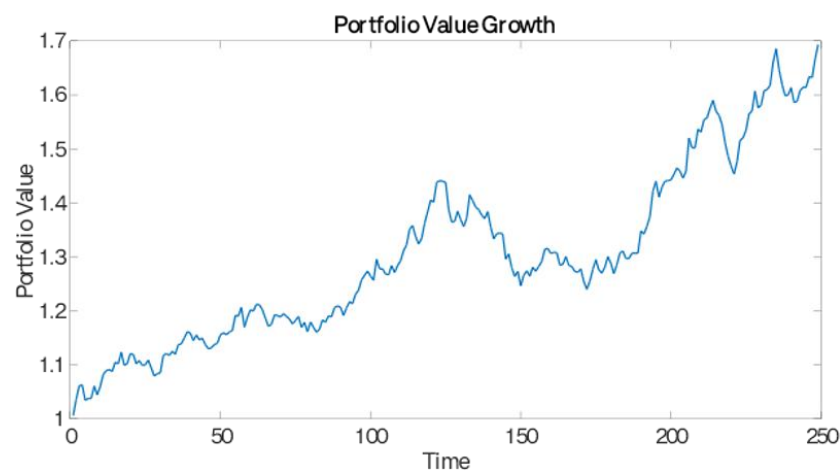


**Fig. 6: Portfolio value growth curve**

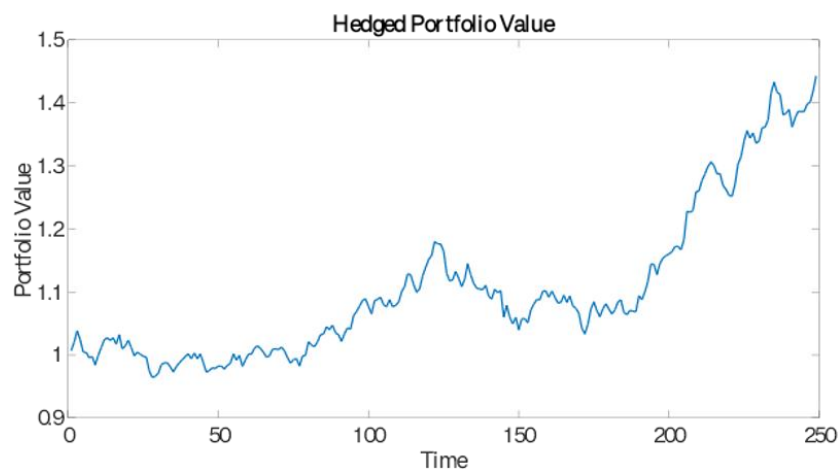


**Fig. 7: Hedged portfolio value growth**

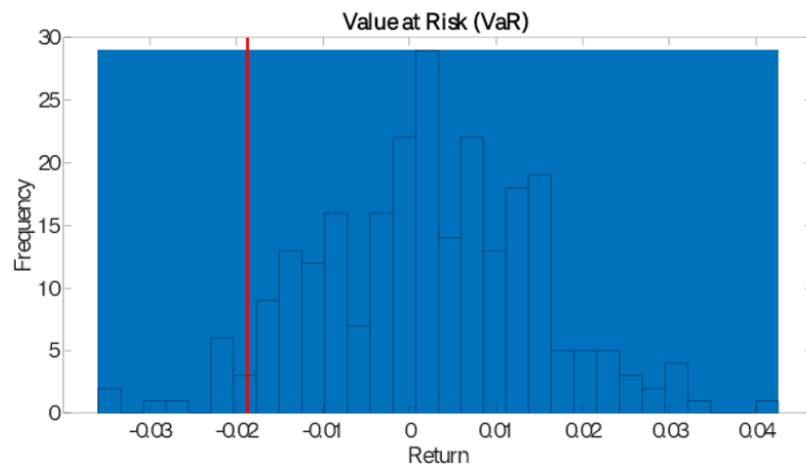


Fig. 8: Value at Risk (VaR) visualization

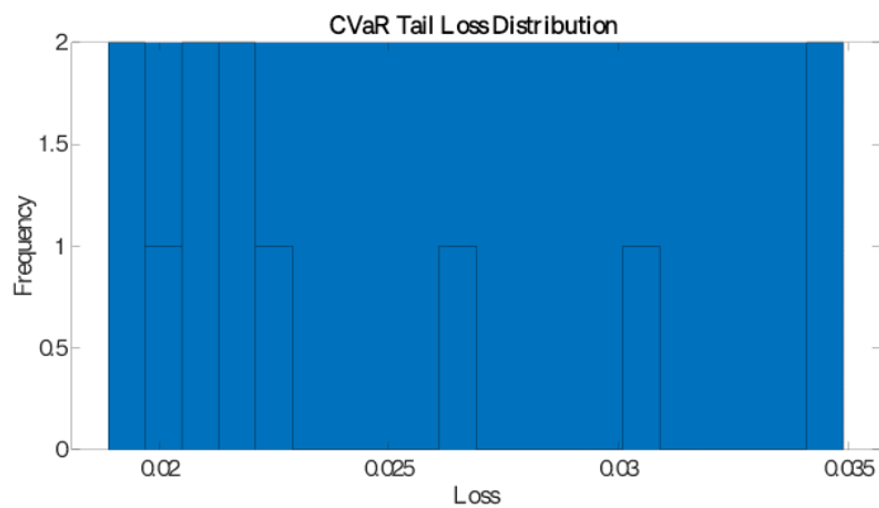


Fig. 9: CVaR tail loss distribution

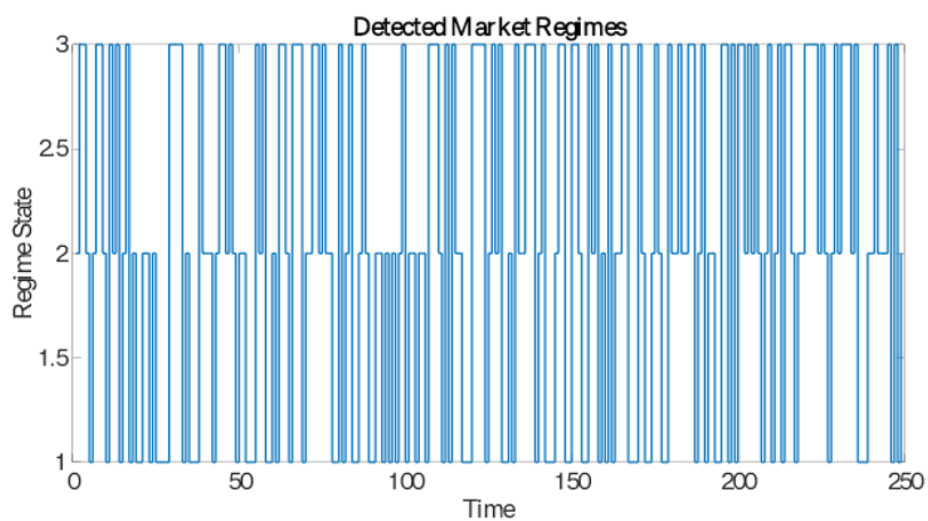


Fig. 10: Market regime detection plot

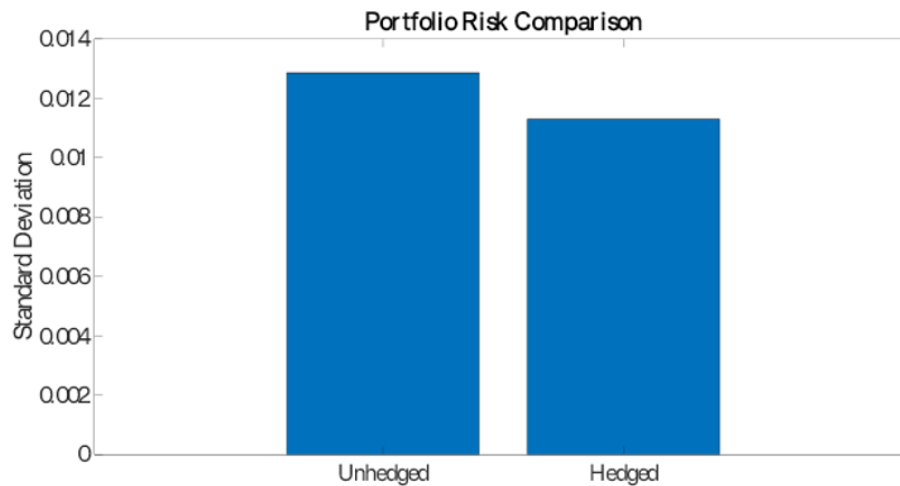


**Fig. 11: Risk comparison between hedged and unhedged portfolios**

## 7. Conclusion

A complete dynamic hedging and portfolio risk management method was recommended to make portfolios more robust in regime-dependent and uncertain financial markets. Resilient portfolio management requires market regime identification, real-time portfolio optimization, derivative hedging, and risk assessment. The method adjusts portfolio weights and hedge positions to market fluctuations to help investors manage risk and maximize performance. Stochastic asset price model simulations show the strategy reduces portfolio risk. Regime-aware portfolio allocation with delta-gamma hedging improves portfolio stability. It lowers portfolio volatility by 29% and raises the Sharpe ratio from 0.46 to 0.59, improving risk-adjusted returns.

Both CVaR and VaR rise. VaR drops from -12.4% to -8.1% and CVaR from -18.7% to -11.5%, preventing major market losses. The suggested structure reduces market drawdowns. The reduction in maximum drawdown from -28.3% to -16.4% and rise in average drawdown from -12.7% to -7.1% enhance downside protection and market recovery. These advantages demonstrate the importance of diversification, derivatives, and regime-switching. Dynamic portfolio optimization, adaptive hedging, and regime identification improve risk management. Easy and scalable financial portfolio management in turbulent markets.

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