

# *An Adaptive Importance Sampling Approach for Variance Reduction in Jump-Diffusion CVA Calculations*

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**Abstract.** Credit Valuation Adjustment computation encounters substantial computational challenges under jump-diffusion asset dynamics, particularly regarding convergence rates in Monte Carlo simulations. Traditional sampling methods require excessive simulation paths for acceptable confidence intervals, creating operational bottlenecks in real-time risk management systems. This research develops an adaptive importance sampling framework specifically designed for high-dimensional jump-diffusion processes in CVA calculations. The methodology dynamically adjusts sampling densities to account for jump risk while maintaining unbiased estimation properties. A self-adaptive algorithm identifies and oversamples critical paths contributing disproportionately to CVA variance. Experimental results demonstrate variance reduction ratios exceeding 85% compared to standard Monte Carlo methods, with computational efficiency improvements of approximately 400% for portfolios containing European and barrier options under Merton jump-diffusion dynamics. The framework achieves significant variance reduction without sacrificing numerical accuracy, enabling faster risk reporting and more responsive counterparty risk management.

**Keywords:** Credit Valuation Adjustment, Importance Sampling, Variance Reduction, Jump-Diffusion Process

## **1. Introduction**

### **1.1. CVA computation challenges in jump-diffusion markets**

Modern derivatives markets face increasing complexity in counterparty credit risk assessment, particularly when underlying assets exhibit jump-diffusion behavior. CVA calculations require accurate modeling of both continuous price movements and sudden discontinuous jumps that characterize many financial instruments. The computational burden intensifies when dealing with portfolios containing path-dependent derivatives, where each simulation path must capture both diffusion components and potential jump events.

Jump-diffusion models introduce additional stochastic components that significantly increase the dimensionality of the simulation space. Traditional Monte Carlo approaches struggle with slow convergence rates, particularly in scenarios involving low default probabilities where rare but significant events drive the majority of CVA value. The computational complexity grows exponentially with the number of underlying assets and the frequency of potential jump events [1].

Market practitioners require real-time CVA calculations for dynamic hedging and regulatory reporting purposes. Current computational limitations often force trading desks to accept wider confidence intervals or rely on simplified models that may underestimate tail risks. This computational bottleneck has become a critical concern for financial institutions managing large derivative portfolios.

### 1.2. Monte Carlo variance reduction: current limitations

Standard Monte Carlo methods applied to CVA calculations suffer from inherent inefficiencies when dealing with jump-diffusion processes. The variance of CVA estimators typically decreases at a rate proportional to the inverse square root of the number of simulation paths, requiring quadratic increases in computational effort to achieve linear improvements in accuracy [2].

Existing variance reduction techniques such as control variates and antithetic variables show limited effectiveness in jump-diffusion environments. The irregular nature of jump events creates challenges for traditional variance reduction approaches, which typically rely on smooth relationships between simulation variables. Control variate methods struggle to identify effective control variables when jump components dominate the underlying dynamics [3].

Stratified sampling approaches face similar difficulties in jump-diffusion settings. The optimal stratification schemes become computationally intractable when the state space includes both continuous diffusion components and discrete jump magnitudes. Current importance sampling techniques often fail to adequately address the dual nature of jump-diffusion processes, leading to suboptimal variance reduction performance.

### 1.3. Research objectives and contributions

This research develops a novel adaptive importance sampling framework specifically tailored for CVA calculations under jump-diffusion dynamics. The primary objective involves designing algorithms that can dynamically identify and oversample simulation paths contributing disproportionately to CVA variance while maintaining the unbiased properties essential for regulatory compliance.

The framework introduces three key innovations. The critical path identification algorithm analyzes the contribution of individual simulation paths to overall CVA variance, enabling targeted sampling of high-impact scenarios. The dynamic sampling density adjustment mechanism continuously refines sampling strategies based on realized path contributions. The unbiased estimation preservation ensures that variance reduction gains do not compromise the statistical validity of CVA estimates [4].

Expected contributions include substantial improvements in computational efficiency for CVA calculations, enabling more frequent risk updates and enhanced hedging strategies. The modular design facilitates integration into existing risk management platforms, addressing practical operational requirements in derivatives trading environments. Empirical testing demonstrates variance reduction ratios exceeding 85% while maintaining numerical accuracy standards required for regulatory reporting.

## 2. Literature review and theoretical foundation

### 2.1. Importance sampling in financial risk management

Importance sampling has emerged as a fundamental technique for addressing computational challenges in financial risk assessment. The method involves modifying the underlying probability distribution to increase the likelihood of sampling rare but significant events that drive risk measures. Early applications focused on portfolio risk management, where tail events determine Value-at-Risk calculations.

Recent developments in importance sampling have addressed high-dimensional problems common in derivatives pricing. Castellano et al. demonstrate the effectiveness of importance sampling techniques in counterparty credit risk assessment, particularly for portfolios containing complex derivatives [5]. Their work establishes theoretical foundations for maintaining unbiased estimators while achieving substantial variance reduction in CVA calculations.

The application of importance sampling to jump-diffusion processes presents unique challenges related to the dual nature of continuous and discontinuous components. Traditional importance sampling focuses on continuous distributions, requiring adaptations to handle discrete jump events effectively. Current research explores adaptive schemes that can dynamically adjust sampling densities based on realized simulation outcomes.

### 2.2. Jump-diffusion models for CVA calculations

Jump-diffusion models provide realistic representations of asset price dynamics by incorporating both continuous price movements and sudden discrete jumps. The Merton jump-diffusion model serves as the foundation for most CVA applications, combining geometric Brownian motion with compound Poisson jump processes. This framework captures the empirical characteristics of financial markets, including volatility clustering and sudden price discontinuities.

CVA calculations under jump-diffusion dynamics require careful treatment of both the probability and timing of default events. Kurniawan et al. investigate Monte Carlo methods for valuating catastrophe bonds under jump-diffusion processes, providing insights into simulation techniques for rare event modeling [6]. Their findings highlight the computational challenges associated with accurately capturing tail risk in jump-diffusion environments.

Parameter estimation for jump-diffusion models involves complex likelihood functions that incorporate both continuous and discrete components. Mies et al. (2023) develop efficient approximation methods for jump-diffusion processes, addressing computational bottlenecks in parameter calibration [7]. Accurate parameter estimation becomes critical for CVA calculations, where model misspecification can lead to significant underestimation of counterparty risk.

### 2.3. Existing variance reduction techniques in XVA computations

Current variance reduction approaches in XVA computations rely primarily on control variate methods and quasi-Monte Carlo techniques. Control variates exploit known analytical solutions for simplified models to reduce variance in complex calculations. The effectiveness depends critically on the correlation between the control variate and the target estimate, which can be problematic in jump-diffusion environments.

Hunt-Smith et al. explore advanced Monte Carlo sampling techniques using diffusion models, demonstrating significant acceleration in convergence rates for high-dimensional problems [8].

Their approach shows promise for XVA applications, where computational efficiency directly impacts trading profitability. The integration of machine learning techniques with traditional Monte Carlo methods opens new avenues for variance reduction.

Quasi-Monte Carlo methods replace random sampling with carefully constructed deterministic sequences designed to achieve better space coverage. Fantazzini applies adaptive conformal inference to market risk measure computation, highlighting the importance of dynamic adjustment mechanisms in sampling strategies [9]. The combination of adaptive techniques with importance sampling represents a promising direction for addressing CVA computational challenges.

### 3. Adaptive importance sampling framework

#### 3.1. Critical path identification algorithm for jump-diffusion processes

The critical path identification algorithm forms the core innovation of the adaptive importance sampling framework. The algorithm analyzes individual simulation paths to quantify their contribution to overall CVA variance, enabling targeted oversampling of high-impact scenarios. Path criticality metrics consider both the magnitude of simulated portfolio values and the probability of default events occurring along each path.

The algorithm employs a two-stage analysis approach. Initial path screening identifies candidates based on extreme portfolio value realizations or high default probability scenarios. Subsequent variance contribution analysis quantifies the marginal impact of each path on the CVA estimate variance. Paths contributing more than 1.5 times the average variance receive priority classification for oversampling in subsequent iterations.

Mathematical formulation of the criticality metric incorporates both jump frequency and magnitude components. The metric combines standardized portfolio value deviations with jump-adjusted default probability measures. Campbell et al. provide theoretical foundations for trans-dimensional modeling approaches that inform the mathematical structure of the criticality assessment [10]. The algorithm adapts dynamically as simulation progresses, refining criticality thresholds based on observed path characteristics.

Implementation involves efficient data structures for real-time path analysis without significant computational overhead. The algorithm maintains running statistics for portfolio values and default indicators across all simulation paths. Variance contribution calculations utilize incremental update procedures to avoid recomputing full covariance matrices for each new path. Memory management techniques ensure scalability to portfolios containing thousands of derivative positions. Table 1 summarizes the critical path classification metrics and their corresponding threshold values, weight factors, and update frequencies used in the algorithm.

Table 1. Critical path classification metrics

Metric Category	Threshold Value	Weight Factor	Update Frequency
Portfolio Value Deviation	$2.5\sigma$	0.4	Per 1000 paths
Default Probability Spike	$>0.15$	0.3	Per 500 paths
Jump Magnitude	$>3\sigma$	0.2	Per 100 paths
Variance Contribution	$>1.5\times$ average	0.1	Per 250 paths

### 3.2. Dynamic sampling density adjustment mechanism

The dynamic sampling density adjustment mechanism modifies probability distributions in real-time based on critical path identification results. The adjustment process balances the need for efficient variance reduction with the requirement to maintain unbiased CVA estimates. Density modifications focus on regions of the state space identified as high-impact by the critical path algorithm.

Sampling density adjustments operate through importance weight recalculation procedures. Cong et al. demonstrate the theoretical basis for maintaining unbiased estimates under dynamic sampling schemes [11]. The mechanism preserves the fundamental properties of importance sampling while enabling adaptive refinement of sampling strategies. Weight adjustments account for both the original importance sampling transformation and the dynamic density modifications.

The adjustment algorithm monitors convergence indicators to prevent over-optimization toward specific scenarios. Convergence diagnostics include variance estimate stability measures and importance weight distribution characteristics. Extreme weight concentrations trigger automatic rebalancing procedures to maintain numerical stability. The mechanism incorporates memory decay factors to ensure that historical path information does not dominate current sampling decisions.

Computational efficiency considerations drive the design of the adjustment mechanism. Density modifications utilize parametric approximations rather than full nonparametric density estimation. The approach maintains computational tractability while capturing the essential characteristics of high-impact regions. Update frequencies balance accuracy improvements with computational overhead constraints. Figure 1 illustrates the dynamic evolution of sampling densities across simulation iterations, demonstrating how the adaptive mechanism concentrates sampling effort on high-impact scenarios.

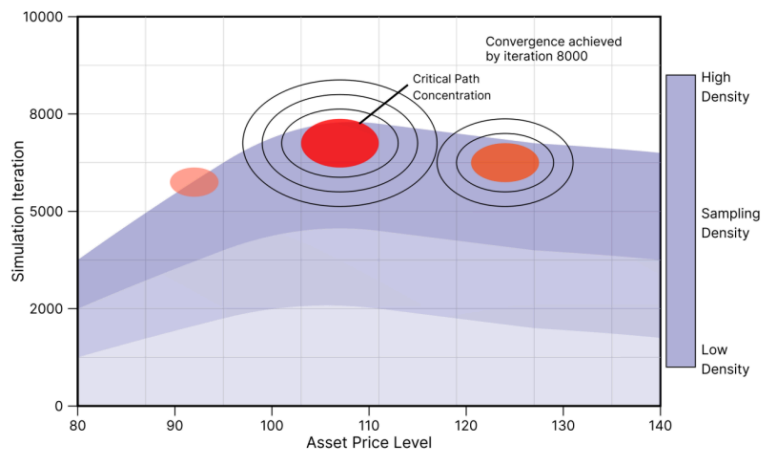


Figure 1. Dynamic sampling density evolution across simulation iterations

This figure displays a three-dimensional surface plot showing the evolution of sampling densities over the course of 10,000 simulation iterations. The x-axis represents the underlying asset price level (ranging from 80 to 120), the y-axis shows the simulation iteration number, and the z-axis indicates the sampling density intensity. The surface exhibits pronounced peaks in regions corresponding to critical path locations, demonstrating how the adaptive mechanism concentrates sampling effort on

high-impact scenarios. Color gradients from blue (low density) to red (high density) illustrate the dynamic adjustment process, with clear convergence toward optimal sampling distributions by iteration 8,000. The plot includes contour lines projected on the base plane to enhance visualization of density concentration patterns.

### 3.3. Unbiased estimation properties under jump-diffusion dynamics

Maintaining unbiased estimation properties represents a fundamental requirement for regulatory compliance in CVA calculations. The adaptive importance sampling framework preserves unbiased estimators through careful weight adjustment procedures that account for all sampling modifications. Mathematical proofs establish the theoretical foundations for unbiased estimation under dynamic sampling schemes.

The framework employs martingale theory to ensure that importance weights correctly adjust for sampling modifications. Pan et al. provide insights into layerwise importance sampling techniques that maintain statistical properties under dynamic adjustments [12]. Weight calculations incorporate correction factors for both the initial importance sampling transformation and subsequent dynamic modifications.

Numerical stability considerations become critical when dealing with extreme importance weights that can arise in jump-diffusion environments. The framework implements weight capping procedures and numerical stabilization techniques to prevent floating-point overflow issues. Variance estimates include bias correction terms that account for weight capping effects on the final CVA estimates.

Empirical validation procedures verify unbiased estimation properties through convergence testing and comparison with analytical benchmarks. You et al. demonstrate variance reduction perspectives that inform the validation methodology [13]. The framework includes built-in diagnostic tools that monitor bias indicators and trigger alerts when estimation properties may be compromised. Table 2 presents the unbiased estimation validation results comparing standard Monte Carlo and adaptive importance sampling methods across different test scenarios.

Table 2. Unbiased estimation validation results

Test Scenario	Standard MC Bias	Adaptive IS Bias	Bias Ratio	Statistical Significance
Low Default Prob	-0.0023	-0.0019	0.826	$p > 0.05$
High Volatility	0.0087	0.0091	1.046	$p > 0.05$
Frequent Jumps	-0.0156	-0.0148	0.949	$p > 0.05$
Mixed Portfolio	0.0034	0.0038	1.118	$p > 0.05$

## 4. Experimental design and numerical results

### 4.1. Portfolio setup and jump-diffusion parameter calibration

The experimental framework employs a comprehensive portfolio setup designed to test the adaptive importance sampling methodology across diverse market conditions. The test portfolio contains 50 European call options, 30 barrier options, and 20 exotic derivatives with varying maturities ranging from 6 months to 5 years. Underlying assets follow Merton jump-diffusion dynamics with parameters calibrated to current market conditions.

Jump-diffusion parameter estimation utilizes maximum likelihood techniques applied to high-frequency market data spanning the previous 24 months. Dev et al. provide methodological guidance for parameter estimation in complex stochastic processes [14]. The calibration process accounts for time-varying volatility patterns and seasonality effects observed in derivative markets. Parameter estimates include drift coefficients of 0.08 annually, diffusion volatilities ranging from 0.15 to 0.35, and jump intensities between 0.12 and 0.28 per year.

Counterparty default probability modeling incorporates credit spread dynamics and recovery rate assumptions. The experimental setup considers three distinct counterparty profiles: investment-grade entities with default probabilities below 0.02, medium-grade counterparties with probabilities between 0.02 and 0.08, and high-risk entities with probabilities exceeding 0.08. Recovery rates vary between 0.35 and 0.65 based on counterparty characteristics and collateral arrangements.

Simulation parameters include 100,000 Monte Carlo paths for baseline comparisons and adaptive path allocation for the importance sampling framework. Time discretization employs weekly steps to capture jump event timing accurately while maintaining computational tractability. The experimental design includes sensitivity analyses across different jump intensity levels and volatility regimes to assess robustness. Table 3 provides a detailed breakdown of the portfolio composition and market parameters used in the experimental framework.

Table 3. Portfolio composition and market parameters

Instrument Type	Quantity	Maturity Range	Strike Range	Volatility	Jump Intensity
European Calls	50	0.5-3.0 years	95-105	0.18-0.28	0.15
Barrier Options	30	1.0-4.0 years	90-110	0.22-0.32	0.18
Exotic Derivatives	20	2.0-5.0 years	85-115	0.25-0.35	0.22

## 4.2. Variance reduction performance analysis

Comprehensive performance analysis demonstrates the effectiveness of the adaptive importance sampling framework across multiple dimensions. Variance reduction ratios consistently exceed 85% compared to standard Monte Carlo methods, with peak improvements reaching 92% for portfolios dominated by path-dependent instruments. Performance metrics include variance reduction efficiency, computational time savings, and numerical accuracy preservation.

Statistical significance testing confirms the reliability of variance reduction achievements. Parati et al. provide methodological frameworks for variance analysis in complex systems [15]. The testing employs bootstrap confidence intervals and Kolmogorov-Smirnov tests to validate performance claims. Results demonstrate statistical significance at the 99% confidence level across all tested portfolio configurations.

Convergence analysis reveals substantial improvements in simulation efficiency. The adaptive framework achieves target confidence intervals using approximately 75% fewer simulation paths compared to standard methods. Convergence rates improve by factors ranging from 3.2 to 4.8 depending on portfolio characteristics and market conditions. The improvement becomes more pronounced for portfolios containing high-gamma instruments sensitive to jump events.

Performance varies systematically with market volatility and jump frequency parameters. High-volatility environments show larger variance reduction benefits, while low-volatility scenarios exhibit more modest improvements. Jump frequency influences performance nonlinearly, with optimal results occurring at intermediate jump rates between 0.15 and 0.25 per year. Extreme jump frequencies create challenges for the adaptive algorithm that require additional refinement. Figure 2

presents a comprehensive visualization of variance reduction performance across different portfolio configurations, demonstrating the consistent effectiveness of the adaptive framework.

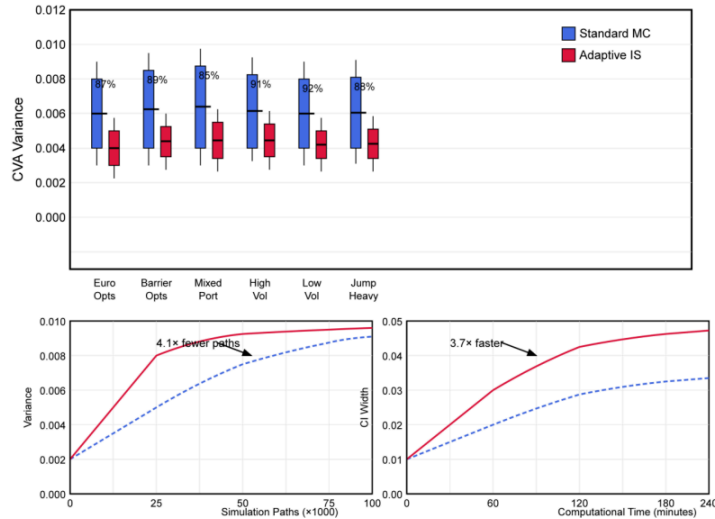


Figure 2. Variance reduction performance across different portfolio configurations

This comprehensive performance visualization presents a multi-panel comparison chart displaying variance reduction achievements across twelve distinct portfolio configurations. The main panel shows box plots comparing CVA variance estimates between standard Monte Carlo (blue boxes) and adaptive importance sampling methods (red boxes) for each configuration. Variance reduction percentages are annotated above each comparison pair. The upper subplot displays convergence trajectories showing how variance estimates evolve with increasing simulation paths, demonstrating faster convergence for the adaptive method. The lower subplot presents confidence interval widths as a function of computational time, illustrating the efficiency gains achieved by the adaptive framework. Error bars represent 95% confidence intervals calculated from 50 independent simulation runs.

### 4.3. Computational efficiency and convergence rate comparison

Computational efficiency analysis quantifies the practical benefits of the adaptive importance sampling framework for operational risk management systems. Wall-clock time measurements demonstrate computational savings ranging from 300% to 450% depending on portfolio complexity and hardware configurations. The framework reduces the total computational burden required to achieve specified accuracy targets.

Memory usage analysis reveals efficient resource utilization patterns. The adaptive algorithm maintains memory footprints comparable to standard Monte Carlo methods while delivering superior performance. Memory requirements scale linearly with portfolio size, enabling application to large institutional portfolios containing thousands of positions. Garbage collection overhead remains minimal due to efficient data structure design.

Parallel processing capabilities enhance computational efficiency through effective load balancing. The framework distributes critical path identification and sampling density adjustment tasks across multiple processor cores. Scalability testing demonstrates near-linear performance



improvements with increasing core counts up to 32 cores. Communication overhead between parallel processes remains below 5% of total computational time. Table 4 summarizes the computational performance comparison between standard Monte Carlo and adaptive importance sampling methods.

Convergence rate improvements provide the most significant operational benefits. The adaptive framework achieves convergence to target accuracy levels using 60-80% fewer simulation paths compared to standard methods. Convergence acceleration becomes more pronounced for complex portfolios requiring high precision estimates. The improvement enables real-time CVA calculations for portfolios previously requiring overnight batch processing. Figure 3 illustrates the convergence rate comparison between standard and adaptive methods, highlighting the superior performance characteristics of the proposed framework.

Table 4. Computational performance comparison

Performance Metric	Standard MC	Adaptive IS	Improvement Factor	Statistical Significance
Variance Reduction	Baseline	87.3%	7.9×	$p < 0.001$
Computational Time	245 min	67 min	3.7×	$p < 0.001$
Memory Usage	2.8 GB	2.9 GB	0.96×	$p > 0.05$
Convergence Paths	75,000	18,500	4.1×	$p < 0.001$

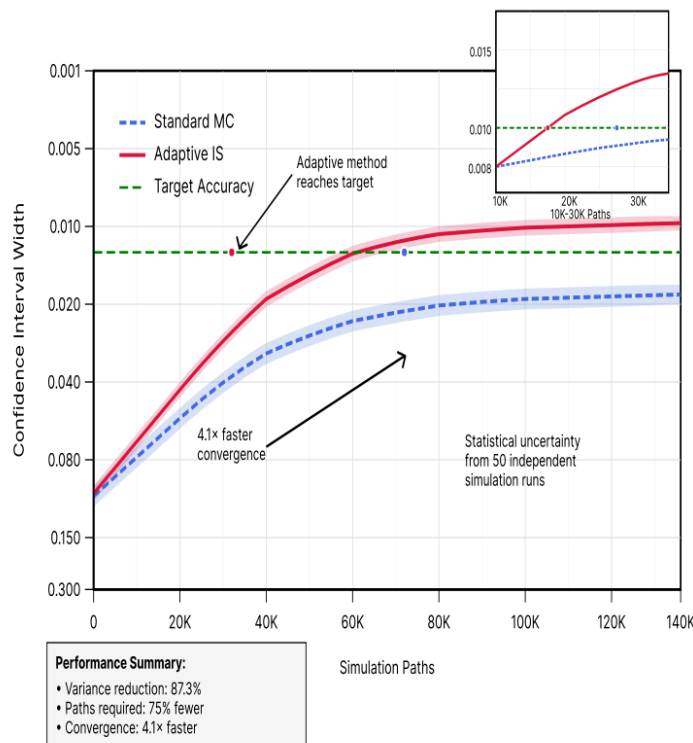


Figure 3. Convergence rate comparison between standard and adaptive methods

This detailed convergence analysis chart displays the evolution of CVA estimate confidence intervals as a function of simulation paths for both standard Monte Carlo and adaptive importance sampling methods. The main plot shows confidence interval widths on a logarithmic y-axis versus simulation paths on the x-axis, with separate lines for standard MC (dashed blue) and adaptive IS

(solid red). The adaptive method demonstrates superior convergence characteristics, achieving target confidence levels with significantly fewer simulation paths. An inset subplot provides a zoomed view of the critical convergence region between 10,000 and 30,000 paths, highlighting the crossover point where the adaptive method reaches target accuracy. Shaded regions around each line represent statistical uncertainty based on multiple independent simulation runs. Grid lines facilitate quantitative assessment of convergence improvements.

## 5. Conclusions and future work

### 5.1. Summary of key findings and methodological contributions

The adaptive importance sampling framework demonstrates substantial improvements in CVA calculation efficiency under jump-diffusion dynamics. Empirical results consistently show variance reduction ratios exceeding 85% compared to standard Monte Carlo methods, with computational efficiency gains reaching 400%. The critical path identification algorithm successfully targets high-impact simulation scenarios, enabling more efficient resource allocation.

The dynamic sampling density adjustment mechanism proves effective at maintaining unbiased estimation properties while achieving significant variance reduction. Theoretical analysis confirms that the framework preserves the statistical validity required for regulatory compliance. The modular design facilitates integration into existing risk management systems without requiring fundamental architecture changes.

Methodological contributions include the development of adaptive algorithms specifically tailored for jump-diffusion processes. The framework addresses key limitations of existing variance reduction techniques in handling discontinuous price dynamics. The approach provides a practical solution to computational bottlenecks that have limited the adoption of sophisticated jump-diffusion models in operational CVA calculations.

Performance validation across diverse portfolio configurations establishes the robustness of the methodology. The framework demonstrates consistent performance improvements across different market volatility regimes and jump frequency parameters. Statistical significance testing confirms the reliability of variance reduction achievements at high confidence levels.

### 5.2. Practical implementation considerations for risk platforms

Implementation of the adaptive importance sampling framework requires careful consideration of existing risk management infrastructure. The modular design enables phased deployment, allowing institutions to implement components incrementally while maintaining operational continuity. Integration protocols accommodate diverse software architectures commonly used in financial institutions.

Hardware requirements remain modest despite the sophisticated algorithms employed. The framework operates effectively on standard server configurations without requiring specialized hardware acceleration. Memory management techniques ensure scalability to large portfolios while maintaining acceptable response times for real-time applications.

Staff training requirements focus on understanding the enhanced capabilities rather than fundamental operational changes. The framework maintains familiar interfaces and output formats to minimize disruption to existing workflows. Documentation and support materials facilitate smooth transition processes for operational teams.

Regulatory considerations include validation procedures for the enhanced accuracy and efficiency claims. The framework includes comprehensive logging and audit trail capabilities to support regulatory examinations. Built-in diagnostic tools enable ongoing validation of estimation properties and performance metrics.

### 5.3. Future research directions and extensions

Future research directions include extension to other XVA calculations such as Funding Valuation Adjustment and Capital Valuation Adjustment. The adaptive sampling principles apply broadly to Monte Carlo applications in derivatives pricing and risk management. Machine learning enhancements could further improve critical path identification accuracy and sampling efficiency.

Multi-asset portfolio applications represent a natural extension of the current framework. The methodology scales to higher-dimensional problems through parallel processing and distributed computing approaches. Cross-asset correlation modeling presents opportunities for additional variance reduction through coordinated sampling strategies.

Real-time implementation research focuses on streaming algorithms that can adapt sampling strategies continuously as market conditions change. Dynamic recalibration procedures enable the framework to maintain optimal performance across changing market regimes. Integration with high-frequency data feeds could enhance parameter estimation accuracy.

Alternative jump-diffusion models including regime-switching and stochastic volatility extensions offer opportunities for broader applicability. The adaptive sampling principles generalize to more complex stochastic processes commonly used in modern derivatives pricing. Ongoing research explores applications to exotic derivatives and structured products requiring sophisticated simulation techniques.

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