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Hybrid Learning-Based Dynamic Optimization for Financial Risk Management:

Integrating Nonlinear Dynamics and Deep Learning

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ABSTRACT

Amid the increasing complexity and dynamic nature of financial markets, accurately capturing market fluctuations and implementing effective risk monitoring remain critical challenges in financial regulation. Traditional differential equation models, while proficient in theoretical derivation and variable representation, face significant limitations in handling high-dimensional, complex data and nonlinear characteristics. Conversely, deep learning technologies, with their robust feature extraction and time-series modeling capabilities, present transformative opportunities for financial data analysis. However, the trade-off between high-precision modeling and interpretability creates notable challenges for single-method approaches. To address these limitations, this study proposes a dynamic optimization framework, CT-BCIR, which integrates traditional differential equations with deep learning methodologies. The framework employs convolutional neural networks (CNNs) to extract local temporal features and long short-term memory networks (LSTMs) to capture long-range dependencies.

KEYWORDS

Financial Regulation, Differential Equations Optimization, CNN, LSTM

INTRODUCTION

Amid the rapid advancement of the global economy, financial markets have become increasingly complex, interconnected, and volatile. The proliferation of high-frequency trading, sophisticated financial derivatives, and digital finance has substantially heightened systemic risk, underscoring the critical need for robust financial regulation. At its core, financial regulation seeks to mitigate risks by supervising market activities, ensuring transparency, and safeguarding stakeholders against fraud and financial instability (Vovk et al., 2020).

Furthermore, the rapid expansion of digital finance and decentralized platforms in recent years has introduced new challenges to the regulatory landscape, including detecting fraudulent activities,

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monitoring market manipulation, and mitigating liquidity risks. Addressing these issues requires not only traditional regulatory frameworks but also the integration of advanced computational tools capable of analyzing vast financial datasets in real time and identifying early indicators of abnormal market fluctuations (Zhang et al., 2024; Zhao et al., 2024). For instance, high-frequency trading in digital asset markets may intensify price volatility, the decentralized structure of decentralized finance platforms can heighten regulatory arbitrage risks, and sudden liquidity contractions may precipitate systemic crises. In this context, financial regulation serves not only as a safeguard against financial crises, but also as a crucial mechanism for fostering economic growth, strengthening market confidence, and ensuring financial equity (Vučinić, 2020). However, achieving these objectives necessitates the development of innovative regulatory strategies that can adapt to the dynamic evolution of financial markets while upholding high standards of accuracy and reliability.

Differential equation models have long served as fundamental tools in financial modeling and regulatory analysis. Classical frameworks, such as the Cox-Ingersoll-Ross (CIR) model, the Vasicek model, and the Merton jump diffusion model, are widely used to characterize interest rate dynamics, volatility patterns, and financial risks. These models provide a robust mathematical foundation for capturing the temporal evolution of financial variables, elucidating mean-reversion properties, stochastic volatility behaviors, and long-term equilibrium trends (Gilens et al., 2021). For instance, the CIR model plays a crucial role in pricing interest rate derivatives and assessing credit risk, while the Vasicek model serves as a basis for modeling interest rate term structures. Despite their theoretical rigor, traditional differential equation models face significant limitations when applied to the high-dimensional and complex data characteristic of modern financial markets. Their reliance on simplifying assumptions—such as market equilibrium, variable independence, and linear relationships—fails to account for the intricate realities of contemporary financial environments. Additionally, these models exhibit limited capacity to process high-frequency data and nonlinear characteristics, reducing their effectiveness in adapting to sudden and unpredictable market fluctuations. Another critical drawback is their dependence on input parameters, where estimation and calibration processes are susceptible to biases, particularly in the presence of poor data quality or heightened market volatility. Consequently, while differential equation models provide a strong theoretical foundation, they are inadequate for addressing the dynamic and multifaceted challenges of today's financial markets (Huang, 2021).

To overcome the limitations of traditional differential equation methods, the integration of deep learning techniques into financial modeling has garnered significant attention in recent years. Deep learning models are particularly effective in capturing nonlinear features and long-term dependencies in time series data, leveraging advanced feature extraction capabilities and their ability to process high-dimensional, complex datasets. However, standalone deep learning models face several challenges, including limited interpretability, a strong dependence on data quality, and a heightened risk of overfitting (Sun & Li, 2023). A promising solution to these challenges lies in a hybrid approach that integrates traditional differential equation methods with deep learning techniques. By leveraging deep learning to optimize the parameters of differential equation models, this approach preserves the theoretical rigor of differential equations while enhancing adaptability and predictive performance. As a result, it improves the accuracy and robustness of financial modeling, offering a more effective framework for addressing the complexities of modern financial markets.

This study introduces the Continuous-Time Brownian Cox-Ingersoll-Ross (CT-BCIR) framework, which combines the strengths of traditional differential equations and deep learning methodologies. By dynamically optimizing model parameters, the framework achieves high-precision predictions and facilitates effective risk monitoring and anomaly detection in financial markets. Compared with traditional methods, the CT-BCIR framework based on the mixed fractional Brownian motion CIR model has significant advantages in parameter optimization and prediction accuracy. Traditional CIR models typically rely on static parameter estimation and are difficult to adapt to the dynamic changes in financial markets. However, CT-BCIR combined with a convolutional neural networks (CNN)-long

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