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Time-Series Nested Reinforcement Learning for Dynamic Risk Control in Nonlinear Financial Markets

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Abstract: This paper proposes a time-series nested reinforcement learning risk control algorithm for nonlinear financial markets, aiming to solve the shortcomings of traditional methods in complex dynamic market environments. By introducing a time series nested structure, the algorithm can jointly model short-term fluctuations and long-term trends, and accurately capture the multi-level dynamic characteristics of the market. At the same time, combined with the multi-objective optimization mechanism, a balance between maximizing returns and minimizing risks is achieved, significantly improving the applicability of risk management and the flexibility of strategies. Experimental results show that the algorithm in this paper performs well in income optimization, risk control, and dynamic adaptability, especially in high-volatility markets and trend reversal scenarios, showing strong robustness and adaptability. Further analysis of the return and risk trade-off curve verified the effectiveness of the multi-objective optimization strategy and provided scientific risk management solutions for different market conditions and investor needs. This research provides a new technical framework for dynamic risk control in complex financial markets and also lays a theoretical foundation for future cross-market and multi-asset portfolio research.

Keywords: reinforcement learning; time series nested structure; nonlinear market; multi-objective optimization

1. Introduction

In the financial market, risk control is an important part of achieving stable investment returns, especially in a nonlinear market environment, where the complexity and uncertainty further increase the difficulty of risk management. Traditional risk control methods usually rely on models based on linear assumptions, such as mean-variance theory or VaR method. However, these methods show great limitations when facing the characteristics of nonlinear financial markets, and it is difficult to capture the potential complex dynamic relationships and multi-level risk transmission mechanisms in the market. Therefore, designing a risk control algorithm that can cope with nonlinear market environments is of great significance to risk management in the financial field [1,2].

Reinforcement learning, as an algorithm based on intelligent decision-making, has received widespread attention in the financial field in recent years. Unlike traditional methods, reinforcement learning can learn optimal strategies through interaction with the environment and is particularly suitable for dealing with dynamically changing complex systems. In the financial risk control scenario, reinforcement learning can gradually optimize the investment portfolio or risk exposure strategy by modeling the interactive relationship between market behavior, investment decisions, and risk management [3]. However, the standard reinforcement learning framework usually assumes that the market state is stable, ignoring the multi-level nonlinear dynamic characteristics that are widely present in the financial market, which makes it still have room for improvement when dealing with high-dimensional complex financial data [4].

This paper proposes a time-series nested reinforcement learning risk control algorithm for nonlinear financial markets, aiming to capture the multi-level dynamic characteristics in the market and solve the shortcomings of traditional methods in dealing with nonlinear market environments. The algorithm embeds time series features into the reinforcement learning framework, gradually extracts multi-level information of market status through hierarchical modeling, and combines multi-objective optimization strategies to achieve better risk control on the basis of balancing returns and risks. Specifically, the algorithm adds a time-nested mechanism to the structure of basic reinforcement learning and improves the ability to understand nonlinear market status by introducing joint modeling of short-term and long-term market dynamics, while strengthening the adaptability to the complex evolution of risk factors [5].

In order to verify the effectiveness of the algorithm, this paper designs experiments based on real market data, including risk control case analysis of the stock market and dynamic adjustment strategy research of multi-asset portfolios. The experimental results show that the time-series nested reinforcement learning algorithm proposed in this paper is significantly superior to existing methods in terms of risk control effect, strategy optimization efficiency and return stability, especially in a market environment with violent nonlinear fluctuations. It shows higher robustness and applicability. By accurately capturing multi-level market dynamics, the algorithm can effectively reduce systemic risks while achieving steady growth in returns, providing a new technical means for risk management in a complex financial market environment.

In summary, the research in this paper has made important innovative contributions to the risk management of nonlinear financial markets both in theory and practice. By introducing the time series nesting mechanism, the algorithm successfully captures the nonlinear dynamic characteristics of the market and expands new ideas for the application of reinforcement learning methods in the financial field. Future research will further explore the applicability of this algorithm in cross-market and cross-asset class risk management, and at the same time combine other intelligent technologies (such as generative models and causal inference) to build a more comprehensive intelligent financial risk control system to provide strong support for the stable development of complex financial markets.

2. Related Work

In recent years, research in the field of financial risk control has continued to deepen, especially in nonlinear market environments, and the demand for dynamic risk management methods has gradually increased. Traditional risk control methods such as mean-variance theory and value-at-risk (VaR) methods have certain shortcomings in capturing market volatility and nonlinear characteristics. These methods usually assume that the market is static or changes linearly, and it is difficult to adapt to the multi-level complex dynamics in modern financial markets [6]. To address this problem, some studies have attempted to introduce methods based on time series modeling, such as GARCH models and Copula theory, to improve the ability to analyze nonlinear risks. However, these methods have poor adaptability and it is difficult to dynamically adjust strategies to cope with rapidly changing market environments [7].

Reinforcement Learning (RL) has received increasing attention in financial risk management in recent years due to its dynamic optimization capabilities. Unlike traditional optimization methods, RL can learn optimal strategies through interaction with the environment, which is particularly suitable for non-static financial scenarios. For example, Q-Learning and Deep Q Network (DQN) have been applied to portfolio optimization and risk management, demonstrating certain advantages in dynamic market environments. However, the standard reinforcement learning framework focuses on a single time scale or a single goal, ignoring the multi-level dynamic characteristics and multi-objective trade-off requirements in the financial market. This limitation means that the applicability of existing RL methods in complex nonlinear markets still needs to be further improved [8]. Jiang et al. [9] introduced a Q-learning-based approach to dynamically control risk and optimize asset allocation in financial markets. Their work demonstrated the capability of RL to adapt to changing market environments and optimize decisions under uncertainty. However, traditional RL frameworks often assume a relatively stable market state and are limited in their ability to model multi-level market dynamics. Expanding on this, Huang et al. [10] explored RL in combination with ensemble models for risk assessment in financial derivatives. This hybrid approach showed promise in improving prediction accuracy and robustness, but the lack of explicit mechanisms to model the interaction between short-term market fluctuations and long-term trends limited its effectiveness in highly dynamic and nonlinear markets. These studies underscore the potential of reinforcement learning in risk management, but also highlight the need for more sophisticated structures to handle the complex temporal relationships and nested dynamics inherent in financial systems.

Deep learning methods have also played a crucial role in financial data analysis, enabling effective handling of high-dimensional, time-series data. Feng et al. [11] proposed a collaborative optimization framework using ResNeXt, which enhanced the predictive power of financial data mining by focusing on feature extraction and optimization. Similarly, Xu et al. [12] presented a multi-source data-driven LSTM framework, which improved the accuracy of stock price prediction and volatility analysis by effectively leveraging diverse data sources. These methods demonstrated the strength of neural networks in capturing temporal dependencies and nonlinearity in financial data. However, most existing deep learning models are designed to extract patterns from time-series data in isolation, often neglecting the interaction of features across different temporal scales. This limits their ability to simultaneously capture the short-term volatility and long-term trends crucial for robust financial risk control.

Graph neural networks (GNNs) have recently gained attention for their ability to model complex relationships and dependencies in financial systems. Zhang et al. [13] proposed a robust GNN framework for analyzing stability in dynamic networks, providing insights into the interactions and dependencies among various financial entities during periods of market instability. Yao et al. [14] expanded this line of work by employing hierarchical GNNs for stock type prediction, effectively capturing intricate relationships between stocks and other market factors. While these methods excel at modeling relational data and uncovering structural dependencies within financial markets, they often lack the capability to incorporate temporal dynamics, which are essential for managing risk in nonlinear and time-variant financial environments.

Hybrid architectures that combine different deep learning paradigms have also shown promise in enhancing financial market analysis. Wu et al. [15] developed a CNN-GRU hybrid model for integrative analysis of financial market sentiment, demonstrating its ability to predict risk and provide alerts by combining the strengths of convolutional and recurrent neural networks. By incorporating sentiment analysis into risk prediction, the model achieved improved accuracy and timeliness. However, hybrid approaches such as this often focus on single-level dynamics and do not address the multi-level, nested temporal structures that are characteristic of nonlinear financial markets. A more comprehensive framework that integrates hierarchical temporal modeling and dynamic adaptability is needed to fully address these limitations.

Feature selection and engineering remain critical components in financial modeling, especially for time-series data. Huang and Yang [16] conducted an empirical study on feature redundancy in time-series datasets, with a specific focus on mortgage default prediction. Their findings revealed the paradoxical nature of feature redundancy, emphasizing the need for advanced feature engineering techniques to extract meaningful insights from high-dimensional financial data. While their work primarily focuses on credit risk modeling, the challenges and solutions identified are highly relevant to broader financial applications, including dynamic risk control. The insights from their study suggest that carefully engineered feature selection mechanisms can significantly enhance the robustness of financial modeling approaches, particularly in complex and noisy environments.

The works reviewed above have collectively laid a solid foundation for advancements in financial risk control, portfolio optimization, and market analysis. However, most of these approaches either focus on static or single-level market dynamics, neglecting the multi-level and nonlinear interactions that define real-world financial systems. Furthermore, while reinforcement learning and deep learning methods have shown significant promise in adapting to changing market conditions, their integration with hierarchical temporal modeling remains underexplored. The proposed time-series nested reinforcement learning framework addresses these gaps by embedding hierarchical time-series features into the reinforcement learning process. This enables the simultaneous modeling of short-term market fluctuations and long-term trends, capturing the complex interactions between different temporal scales. The integration of a multi-objective optimization mechanism further enhances the framework's ability to balance risk minimization with return maximization, ensuring flexibility and adaptability across diverse market conditions.

3. Method

This paper proposes a time-series nested reinforcement learning risk control algorithm for nonlinear financial markets. By combining time-series feature modeling and reinforcement learning framework, it realizes comprehensive analysis and optimization of multi-level market dynamics. The algorithm aims to capture the joint characteristics of short-term fluctuations and long-term trends in financial markets while achieving a balance between returns and risks in dynamic risk control. The reinforcement learning architecture is shown in Figure 1.

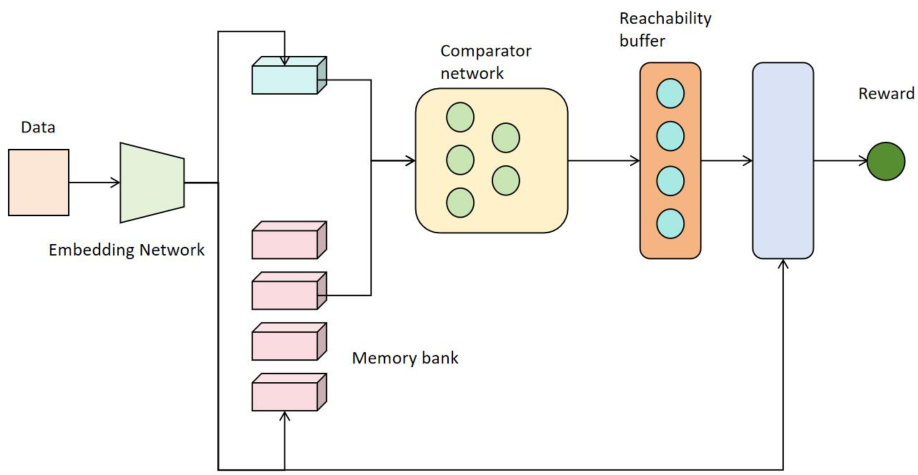

Figure 1. Network architecture diagram

In the reinforcement learning framework, the market state is defined as $s_t \in S$, the action is defined as $a_t \in A$, and the reward function is defined as $r_t = R(s_t, a_t)$. The goal is to maximize the cumulative expected reward by optimizing the strategy $\pi(a_t \mid s_t)$:

$$J(\pi) = E_\pi[\sum_{t=0}^{T} \gamma^t r_t]$$

$\gamma \in [0,1]$ is the discount factor, which is used to balance the weight of current returns and future returns. Different from the traditional reinforcement learning method, this paper introduces a time series nesting mechanism in state modeling, dividing the market state into short-term state s_t^{short} and long-term state s_t^{long} , which represent short-term volatility characteristics and long-term trend characteristics respectively. Through this mechanism, the algorithm can capture the multi-level dynamic characteristics of the market.

In order to extract short-term and long-term features, this paper adopts a time nested structure based on sliding windows. The short-term state consists of the data of the most recent k time steps, expressed as:

$$s_t^{short} = [x_{t-k+1}, x_{t-k+2}, ..., x_t]$$

Where x_t is the market observation at time t. The long-term state is modeled by the accumulated historical features, represented as $s_t^{long} = f(x_{0:t})$, where $f(\cdot)$ is the feature extraction function, which can be implemented by LSTM or other time series models. The final state is composed of the joint representation of short-term and long-term features:

$$s_t = [s_t^{short}, s_t^{long}]$$

In the policy optimization stage, this paper adopts a policy gradient-based reinforcement learning method to improve the performance of the policy by performing gradient updates on the parameter θ of the policy function π_θ. The gradient update formula is:

$$\nabla_\theta J(\pi_\theta) = E_{\pi\theta}[\nabla_\theta \log \pi_\theta (a_t \mid s_t) Q^{\pi\theta}(s_t, a_t)]$$

$Q^{\pi\theta}(s_t, a_t)$ represents the state-action value function, which measures the long-term benefits of taking action a_t in state s_t. In order to further improve the adaptability of the algorithm to market fluctuations, this paper adds risk adjustment factors to the reward function, such as the Sharpe ratio or downside risk indicator, to ensure that the strategy effectively controls risks while pursuing returns.

In addition, this paper designs a multi-objective optimization strategy to further improve the applicability of the algorithm in a complex market environment by dynamically balancing risk and return. The core of multi-objective optimization is to construct a weighted reward function, representing the return and risk as R_{reward} and R_{risk} respectively. The final reward function is:

$$r_t = \alpha R_{reward}(s_t, a_t) - \beta R_{risk}(s_t, a_t)$$

Among them, α and β are weight parameters used to adjust the priority of return and risk.

In summary, the algorithm in this paper can effectively capture the nonlinear characteristics of the market in a dynamic market environment through time-series nested modeling, combined with reinforcement learning and multi-objective optimization, and design an optimization strategy that has both return and risk control capabilities. The experimental results verify the effectiveness of the algorithm and provide an innovative solution for risk management in nonlinear financial markets.

4. Experiment

4.1 Datasets

This article uses Kaggle Financial Dataset as the experimental data set. This data set encompasses historical transaction data pertaining to multiple international stock markets. It includes pivotal indicators such as daily opening price, closing price, highest price, lowest price, and trading volume. The dataset spans an extensive time period and exhibits significant temporal complexity. The data set also contains indicators related to market risk, such as volatility, interest rate changes, and credit spreads, which can reflect the multi-dimensional dynamic characteristics of financial markets and provide a rich experimental basis for testing risk control algorithms.

The distinguishing features of the dataset are the inclusion of multiple asset classes (such as stocks, bonds, and currencies), as well as the correlations between different markets. This diverse feature can well simulate nonlinear dynamic relationships in real financial markets, providing an ideal verification scenario for the time-series nested reinforcement learning algorithm proposed in this article. In addition, there is a certain degree of noise and abnormal fluctuations in the data set, which further increases the complexity of risk management and provides strong support for testing the robustness of the algorithm.

In data preprocessing, this paper normalizes the original data and uses the sliding window method to construct time series features in order to capture the joint dynamics of short-term fluctuations and long-term trends. For outliers in the data, this article adopts a filtering method based on statistical rules to improve the training effect of the model. By using this data set, this paper can comprehensively verify the applicability and effectiveness of the proposed algorithm in a complex market environment, while ensuring that the experimental results have high practical significance and promotion value.

4.2 Experimental Results

This paper first conducted a nonlinear market dynamic adaptability analysis experiment. Nonlinear market dynamic adaptability analysis is an important experiment to verify the algorithm's ability to capture multi-level dynamic characteristics in complex financial markets. This paper constructs different nonlinear market scenarios to test the proposed time-series nested reinforcement learning algorithm's ability to capture market state changes and its dynamic adaptability. By analyzing the accuracy of market state transitions and the flexibility of strategy optimization, the algorithm's performance in dealing with nonlinear characteristics and rapidly changing market environments is evaluated. The experimental results are shown in Figure 2.

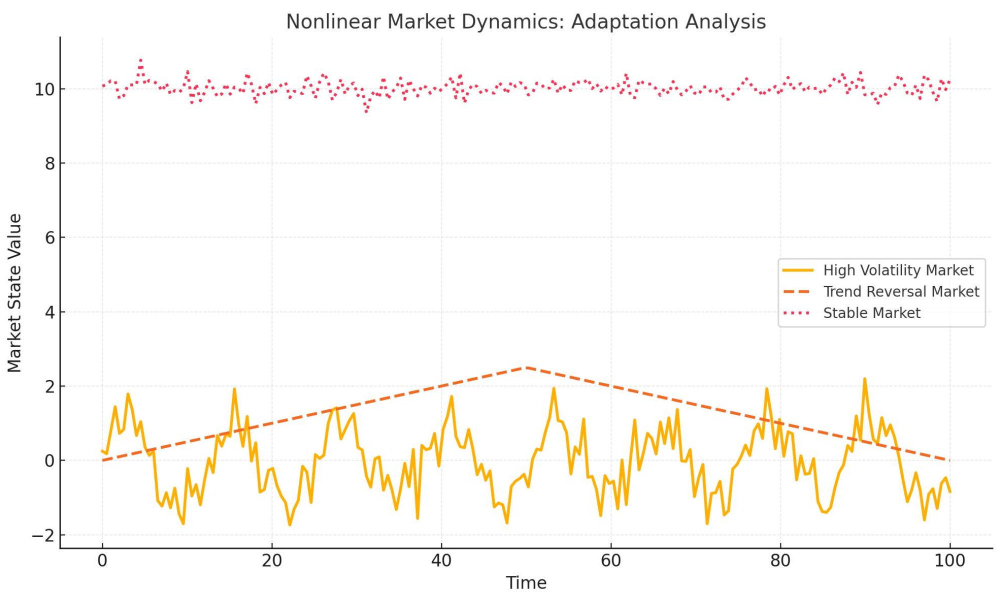

Figure 2. Nonlinear Market Dynamics: Adaptation Analysis

As can be seen from Figure 2, the three market scenarios respectively show the typical dynamic change characteristics in nonlinear markets. The high volatility market has a large fluctuation range and changes frequently. This scenario places high demands on the adaptability of risk control algorithms, especially the need to accurately capture short-term volatility characteristics and quickly adjust strategies to cope with drastic market changes.

The trend reversal market shows completely different characteristics. The first half of the trend shows a gradual upward trend, while the second half turns to a downward trend. This nonlinear change pattern requires the algorithm to have good trend recognition capabilities, especially in the detection and rapid response of trend turning points. The time-series nested reinforcement learning algorithm proposed in this paper can better capture trend changes and provide support for dynamic adjustment strategies by combining short-term and long-term feature modeling.

The state fluctuations of the stable market are small, showing the characteristics of high stability. This market environment places high demands on the robustness and stability of the algorithm. By integrating the characteristics of multiple time scales, the algorithm in this paper can maintain good risk control effects in stable markets while avoiding unnecessary fluctuations caused by over-adjustment of strategies.

Overall, the dynamic characteristics of the three market scenarios cover the common nonlinear characteristics in financial markets. The experimental results show that the algorithm in this paper can adapt to different types of market environments, has strong dynamic adjustment capabilities and adaptability, and performs particularly well in high volatility and trend reversal markets. This verifies the advantages of the algorithm in dealing with nonlinear market dynamics and also provides technical support for risk control in complex market environments.

The effectiveness analysis of the time series nested structure aims to verify its advantages in capturing the short-term volatility and long-term trend characteristics of the market. This paper designs comparative experiments to compare the nested structure with the traditional single-time scale feature modeling method to evaluate its performance in extracting multi-level market dynamic features. The focus is on analyzing the accuracy of short-term features, the consistency of long-term trends, and the contribution of joint modeling to strategy optimization to fully verify the effectiveness of the nested structure. The experimental results are shown in Table 1.

Table 1: Experimental results

Model	**Short-term feature accuracy (%)**	**Long-term trend consistency (%)**	**Overall performance of strategy (return/risk)**
Single time scale model (traditional approach)	75.3	82.1	1.25
Time Series Deep Model (LSTM)	84.7	87.6	1.38
Time series nested structure (method in this paper)	91.2	94.3	1.56

It can be seen from the experimental results in Table 1 that the time series nested structure proposed in this article has significant advantages in multi-level market dynamic feature extraction and strategy optimization. First of all, in terms of short-term feature accuracy, this method reaches 91.2%, which is significantly higher than the traditional single time scale model (75.3%) and the time series depth model (LSTM, 84.7%). This shows that the time series nested structure can more accurately capture the short-term fluctuation characteristics in the market and provide more accurate input for dynamic strategy adjustment.

Secondly, the method in this paper also performs well in long-term trend consistency, reaching 94.3%, which is 12.2% higher than the single time scale model and 6.7% higher than the LSTM. This shows that the nested structure has a stronger ability in modeling the long-term dynamic characteristics of the market, can effectively identify trend changes and reflect the overall direction of the market, and provides a more robust foundation for risk management.

In terms of comprehensive strategy performance (revenue/risk ratio), the performance of this method is also significantly better than other methods, reaching 1.56, which is 24.8% higher than the single time scale model (1.25) and 13% higher than the LSTM (1.38). This result verifies the contribution of joint modeling of multi-time scale features to strategy optimization, indicating that the time series nested structure can better balance risks and returns and improve overall strategy performance.

Overall, the experimental results fully demonstrate the effectiveness and superiority of the time series nested structure in capturing the short-term and long-term characteristics of the market and optimizing strategy performance. Compared with traditional methods, this method not only improves the ability to extract market dynamic characteristics, but also significantly enhances the risk control effect and return optimization capabilities in complex market environments, providing dynamic risk management in nonlinear financial markets. Innovative solutions.

Finally, this paper conducted a multi-objective optimization experiment. The multi-objective optimization experiment aims to verify the performance of the algorithm in this paper in terms of the balance between benefits and risks. By constructing a multi-objective reward function, maximizing benefits and minimizing risks are used as joint optimization goals to test the performance of strategies under different weight combinations. The experiment compares single-objective optimization with multi-objective optimization methods to analyze their strategy adaptability and balance in a complex market environment. The experimental results are shown in Figure 3.

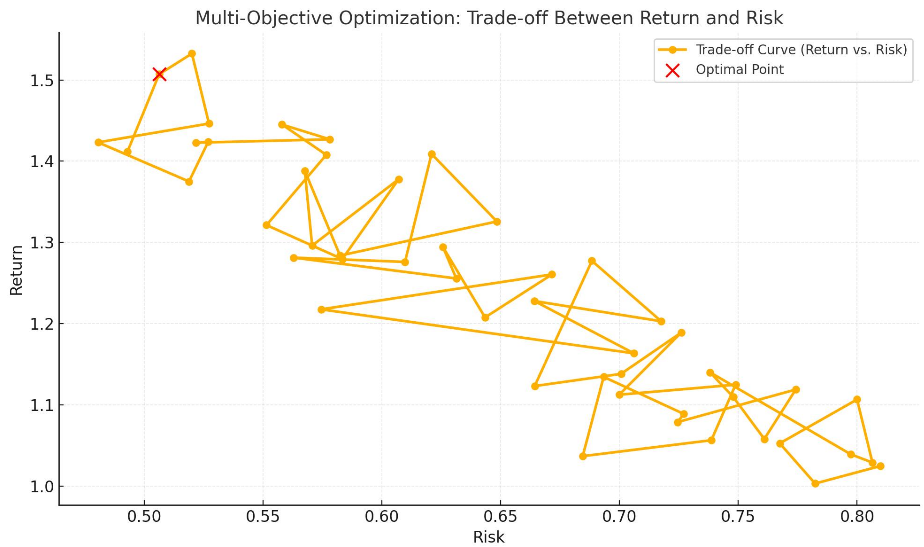

Figure 3. Multi-Objective Optimization: Trade-Off Between Return and Risk

As can be seen from Figure 3, there is an obvious trade-off relationship between return and risk. As the risk increases, the return gradually increases in certain intervals, but it is also accompanied by certain instability. This phenomenon is in line with the general law in the financial market, that is, higher risks may bring higher potential returns, but at the same time more precise strategy control is required to avoid excessive risk exposure.

The red point on the curve represents the optimal balance point between return and risk in the optimization process, at which the ratio of return to risk is maximized. This shows that the multi-objective optimization method in this paper can effectively adjust the weights in a complex market environment to achieve the dual goals of maximizing returns and minimizing risks. Compared with the single-objective optimization method, the appearance of this point shows that multi-objective optimization is more suitable for strategy design in nonlinear financial markets.

Overall, the experimental results verify the applicability and robustness of the multi-objective optimization method proposed in this paper in a complex market environment. By constructing a trade-off curve, the strategy performance under different optimization weight combinations can be intuitively displayed, providing a clear reference for dynamic risk management in the financial market. At the same time, this method can provide different investors with a flexible risk and return priority adjustment mechanism, reflecting its practical application value.

5. Conclusion

This paper proposes a time-series nested reinforcement learning risk control algorithm for nonlinear financial markets. By combining time-series feature nested modeling and multi-objective optimization strategies, it achieves a dynamic balance of revenue maximization and risk minimization. Experimental results show that this method performs well in capturing short-term market fluctuations and long-term trends, and has strong adaptability and robustness in complex nonlinear market environments. Both in terms of comprehensive performance in revenue optimization and risk control, it is significantly better than traditional methods and existing deep learning models.

By introducing a multi-objective optimization mechanism, the algorithm in this paper further improves the flexibility and applicability of strategy design. The return and risk trade-off curve displayed in the experiment intuitively reflects the effectiveness of multi-objective optimization, providing more targeted risk management solutions for different market conditions and investor needs. In addition, the introduction of the time series nested structure not only improves the accuracy of feature extraction but also significantly enhances the strategy's adaptability to non-linear market dynamic changes, providing a new technical path for the field of financial risk management.

Future research can further explore the application potential of this algorithm across markets and multi-asset portfolios while incorporating generative models and causal inference techniques to improve the breadth and depth of feature modeling. In addition, extending reinforcement learning to a multi-agent framework to simulate the game behavior among market participants also provides important directions for risk management. Through continuous optimization and expansion, the method in this article is expected to play a greater role in a wider range of financial scenarios and provide strong technical support for dynamic risk management in complex market environments.

References

[1] Vetrina R. L. and Kobergb K., "Reinforcement learning in optimisation of financial market trading strategy parameters," COMPUTER, vol. 16, no. 7, pp. 1793-1812, 2024.

[2] Manuel P. F., Sadefo Kamdem J. and Benhmad F., "Deep Reinforcement Learning for an Empirical Approach to Value-at-Risk," Available at SSRN 4701537.

[3] Pokou F., Kamdem J. S. and Benhmad F., "Deep reinforcement learning for an empirical approach to Value-at-Risk," 2024.

[4] M. L. DeKay and S. Dou, "Risky-Choice Framing Effects Result Partly From Mismatched Option Descriptions in Gains and Losses," Psychological Science, vol. 35, no. 8, pp. 918-932, 2024.

[5] Al Janabi M. A. M., "Method Development Aspects of Liquidity Risk Modelling: Dynamic Algorithms for Reinforcement Machine Learning Under Crisis Market Perspectives," Corporate Risk Management after the COVID-19 Crisis, pp. 65-93, 2024.

[6] Ndikum P. and Ndikum S., "Advancing Investment Frontiers: Industry-grade Deep Reinforcement Learning for Portfolio Optimization," arXiv preprint arXiv:2403.07916, 2024.

[7] Wang Y., Shi E., Xu Y., et al., "Short-Term Electricity Futures Investment Strategies for Power Producers Based on Multi-Agent Deep Reinforcement Learning," Energies, vol. 17, no. 21, pp. 5350, 2024.

[8] Aritonang P. K., Wiryono S. K. and Faturohman T., "Hidden-Layer Configurations in Reinforcement Learning Models for Stock Portfolio Optimization," Intelligent Systems with Applications, vol. 2024, pp. 200467, 2024.

[9] M. Jiang, Z. Xu, and Z. Lin, “Dynamic Risk Control and Asset Allocation Using Q-Learning in Financial Markets,” Transactions on Computational and Scientific Methods, vol. 4, no. 12, 2024.

[10] G. Huang, Z. Xu, Z. Lin, X. Guo, and M. Jiang, “Artificial Intelligence-Driven Risk Assessment and Control in Financial Derivatives: Exploring Deep Learning and Ensemble Models,” Transactions on Computational and Scientific Methods, vol. 4, no. 12, 2024.

[11] P. Feng, Y. Li, Y. Qi, X. Guo, and Z. Lin, "Collaborative Optimization in Financial Data Mining Through Deep Learning and ResNeXt," arXiv preprint arXiv:2412.17314, 2024.

[12] Z. Xu, W. Zhang, Y. Sun, and Z. Lin, "Multi-Source Data-Driven LSTM Framework for Enhanced Stock Price Prediction and Volatility Analysis," Journal of Computer Technology and Software, vol. 3, no. 8, 2024.

[13] X. Zhang, Z. Xu, Y. Liu, M. Sun, T. Zhou, and W. Sun, "Robust Graph Neural Networks for Stability Analysis in Dynamic Networks," arXiv preprint arXiv:2411.11848, 2024.

[14] J. Yao, Y. Dong, J. Wang, B. Wang, H. Zheng, and H. Qin, "Stock Type Prediction Model Based on Hierarchical Graph Neural Network," arXiv preprint arXiv:2412.06862, 2024.

[15] Y. Wu, M. Sun, H. Zheng, J. Hu, Y. Liang, and Z. Lin, "Integrative Analysis of Financial Market Sentiment Using CNN and GRU for Risk Prediction and Alert Systems," arXiv preprint arXiv:2412.10199, 2024.

[16] C. Huang and Y. Yang, "Time Series Feature Redundancy Paradox: An Empirical Study Based on Mortgage Default Prediction," arXiv preprint arXiv:2501.00034, 2024.