Frontiers in Business, Economics and Management
ISSN: 2766-824X | Vol. 17, No. 3, 2024

Research Progress in Option Pricing Methods

-- A Review of Machine Learning and Neural Network Applications

Shangwang Xiao

Room 578, Building 1, School of Economics, Shanghai University, 99 Shangda Road, Shanghai, 200444, China

Abstract: In recent years, option pricing has garnered significant attention as a critical topic in financial engineering. Classical models, such as Black-Scholes, exhibit limitations in accurately capturing the dynamic changes in complex market environments. Consequently, machine learning techniques and neural network methods have emerged as pivotal research directions in option pricing. This paper provides a systematic review of the advances in option pricing based on optimization methods, machine learning techniques, and neural network models. Optimization methods, incorporating techniques like genetic algorithms and particle swarm optimization, significantly enhance the adaptability and accuracy of classical models. Machine learning methods, such as support vector machines and decision trees, demonstrate their advantages in nonlinear data modeling. Neural networks and deep learning models, with their robust nonlinear fitting capabilities, have become central tools in pricing complex financial products. Additionally, this review summarizes the application of hybrid models and evaluates the strengths and weaknesses of various approaches in practical applications. Finally, the paper discusses future research directions, including the integration of reinforcement learning techniques, improvement in model interpretability, and deep fusion of heterogeneous multi-source data. This work aims to provide theoretical references and technical support for further research in the field of option pricing.

Keywords: Option Pricing, Machine Learning, Neural Networks, Hybrid Model.

1. Introduction

The financial derivatives market, as a crucial component of the modern financial system, has been expanding in both scale and complexity along with the development of global financial markets. As one of the core products in the derivatives market, options have attracted significant attention from market participants due to their ability to effectively hedge risks and enhance capital efficiency. However, accurately pricing options remains a challenging task. Classical option pricing models, such as the Black-Scholes model, have provided an essential foundation for financial theory. Nevertheless, these models often rely on assumptions of simplified market conditions, such as constant volatility and normal price distributions, which do not typically hold in real-world markets.

To address the limitations of classical models, machine learning techniques have emerged as a research focus in the field of option pricing in recent years. With their powerful data processing capabilities and flexibility, machine learning methods can capture nonlinear relationships and complex dynamic features in the market. In particular, neural network techniques and deep learning models have shown remarkable performance in financial data modeling. Furthermore, researchers have attempted to combine traditional option pricing models with modern optimization methods, introducing techniques such as genetic algorithms and particle swarm optimization to improve pricing accuracy and adaptability. Additionally, the integration of multiple machine learning models, such as combining support vector machines with neural networks, has provided new perspectives for option pricing.

The main objective of this review is to systematically summarize the research progress in option pricing based on machine learning and neural networks. The paper will explore four key areas: first, the research on optimization methods, analyzing the integration of traditional option pricing models with modern optimization techniques; second, the application of machine learning methods (such as support vector machines and decision trees) in option pricing; third, a summary of the innovations and applications of neural networks and deep learning models in modeling complex financial data; and lastly, an overview of current hybrid methods that combine multiple models to overcome the limitations of individual models and improve pricing precision. Through this summary, the paper aims to present the latest developments in the field and provide insights into potential future research directions.

The structure of this paper is as follows: Chapter 2 reviews the integration of traditional option pricing models with optimization methods; Chapter 3 discusses the application of machine learning models, excluding neural networks, in option pricing; Chapter 4 focuses on the application and advantages of neural networks and deep learning technologies in option pricing; Chapter 5 analyzes the hybrid application of multiple models; and finally, the conclusion and outlook section presents potential future research directions in the field of option pricing.

This review aims to provide a clear reference framework for financial engineering researchers through systematic classification and analysis, and further promote the practical application of machine learning and deep learning technologies in financial markets.

2. Optimizing Option Pricing Models

Traditional option pricing models, such as the Black-Scholes model, hold a significant position in financial market theory. These models provide relatively simple descriptions of option price changes based on analytical solutions derived from assumptions. However, in practical applications, the complexity and uncertainty of financial markets often make these traditional models face many limitations. For example,

dynamic changes in volatility, asset price jumps, and market nonlinearities are difficult to accurately reflect through traditional models. As a result, researchers have begun to incorporate modern optimization techniques, such as genetic algorithms, particle swarm optimization, Bayesian methods, and their combination with neural networks, to optimize these models.

The introduction of optimization techniques has enabled traditional models to demonstrate greater adaptability in more complex market environments. For instance, genetic algorithms perform well in global search and parameter optimization, allowing volatility stochastic models like the Heston model to more accurately describe market dynamics. In addition, the rapid development of neural network technology has also provided the possibility to improve classical models. Neural networks can capture nonlinear features and automatically calibrate model parameters through large-scale data training, effectively improving pricing accuracy. In recent years, these optimization techniques have not only helped traditional models overcome many limitations but also expanded their applications in high-dimensional markets and complex derivative pricing.

(Andreou et al., 2008) proposed an option pricing method that combines artificial neural networks with parametric models. The paper discusses how to combine neural networks with the traditional Black-Scholes model, using implied parameters (such as implied volatility) to enhance the accuracy of option pricing. Experimental results show that the combination of neural networks with parametric models effectively improves option pricing accuracy, especially when dealing with significant market volatility, as neural networks can capture more nonlinear information, thereby providing more accurate pricing. This method provides a new approach for option pricing and trading, especially in dynamic market environments, as it can better adapt to market changes.

(Guo, 2016) proposed a numerical solution method for the Black-Scholes option pricing model optimized by neural networks. The paper improves the adaptability of the traditional model under complex market conditions by introducing neural networks to optimize the Black-Scholes model. By automatically adjusting the model's parameters using neural networks, the method can more accurately solve the option pricing problem, especially in handling complex volatility and nonlinear market data, outperforming traditional numerical methods. This research provides a new perspective on option pricing and demonstrates the application potential of neural networks in financial modeling.

(Das & Padhy, 2017) proposed a new hybrid model combining parameterization with machine learning, using homogeneity hints for European-style index option pricing. The paper first analyzes the limitations of traditional parameterized methods and machine learning models in option pricing, and then presents an innovative hybrid model that enhances its predictive ability by introducing homogeneity hints. The study shows that the hybrid model not only improves the accuracy of option pricing but also exhibits greater adaptability when handling nonlinear market data. Through experimental analysis on multiple datasets, the authors found that this hybrid model outperformed traditional parameterized models and single machine learning models in option pricing. Especially when handling complex financial products and unstable market conditions, the hybrid model showed higher stability and predictive accuracy. The paper also discusses the computational efficiency and scope of application of the model, recommending that appropriate parameter settings be chosen based on market characteristics in real-world applications.

(L. Zhang & Zhang, 2018) proposed a hybrid neural network option pricing method optimized by the Heston model and genetic algorithms. The paper combines the stochastic volatility of the Heston model with the global search ability of genetic algorithms to optimize the performance of neural networks in option pricing. By optimizing the weights of the neural network with genetic algorithms, the model can more accurately capture nonlinear relationships in the market and improve pricing accuracy. Experimental results show that this hybrid model has higher accuracy than traditional models when handling complex option pricing problems, especially under high-volatility market conditions, demonstrating strong advantages.

(Eskiizmirliler et al., 2021) explored using feedforward neural networks to solve the Black-Scholes equation. The paper proposes that feedforward neural networks can effectively approximate the solution of the classical Black-Scholes equation, especially in high-dimensional and complex option pricing problems, exhibiting stronger flexibility than traditional analytical methods. Through experimental validation, the authors demonstrated the application of neural networks in option pricing, particularly under multi-asset and multidimensional data conditions, providing fast and accurate predictions.

(Santos & Ferreira, 2024) studied how neural networks learn the Black-Scholes equation for option pricing. The paper proposed a new method using neural network models to approximate the solution of the Black-Scholes equation and apply it to option pricing. Through experiments, the authors demonstrated that neural networks could effectively approximate the traditional analytical solution, particularly in high-dimensional and complex option pricing problems, showing stronger adaptability and accuracy than traditional numerical methods. This research showcases the potential of neural networks in solving classic financial problems and provides new insights for the application of deep learning in future financial modeling.

(Mehrdoust, 2024) proposed a method using artificial neural networks (ANNs) for calibrating European option pricing models under uncertain environments. The paper introduced neural networks to address uncertainty factors in the market, proposing a flexible model calibration approach. The experiments showed that ANN could more accurately calibrate option pricing models in the presence of market volatility, incomplete information, and other uncertainties, thus providing more precise option pricing. This method offers a new approach for optimizing and adjusting option pricing, especially in complex and dynamic market environments.

(Hainaut & Casas, 2024) proposed an option pricing method based on a physics-inspired neural network applied to the Heston model. The paper combined the Heston model with neural networks and used physics-inspired ideas to design a new network architecture to improve option pricing accuracy. The experiments showed that this method could effectively handle the stochastic volatility in the Heston model, and particularly in processing complex financial market data, neural networks provided more accurate pricing results than traditional methods. This study demonstrated the application potential of physics-inspired neural networks in financial modeling, particularly in the extension of volatility

models.

(Moreno T et al., 2024) explored the use of neural networks combined with the nonlinear Feynman-Kac theorem in financial option pricing. The paper proposed combining neural networks with the Feynman-Kac theorem to solve financial option pricing problems. Through this method, the authors were able to address the nonlinear features in option pricing and use neural networks for fast and efficient computation. Experimental results indicated that this method was more accurate and efficient than traditional analytical methods, particularly in high-dimensional and nonlinear option pricing problems. The research provided a new perspective on option pricing and demonstrated the significant advantages of neural networks in solving complex mathematical models.

(Benth et al., 2024) investigated the use of neural networks for pricing floating options in Hilbert space. The paper transformed the option pricing problem into a mathematical problem in Hilbert space and solved it using neural networks. The experiments showed that this approach could handle high-dimensional and complex option pricing problems, particularly for floating options, providing more efficient and accurate pricing results compared to traditional numerical methods. This research demonstrated the application potential of neural networks in financial mathematics and offered a new solution for pricing complex financial products.

The integration of optimization techniques with traditional option pricing models has significantly expanded the applicability of theoretical models in real financial markets. These studies show that optimization methods not only improve pricing accuracy but also demonstrate robustness in high-volatility and complex market environments. For example, the combination of genetic algorithms and neural networks offers new ideas for solving nonlinear pricing problems, while Bayesian learning-based model calibration methods provide a powerful tool for option pricing under uncertain environments. Additionally, research shows that the introduction of optimization techniques significantly enhances the performance of traditional models in high-dimensional financial products (such as basket options and multi-asset options).

However, these methods also face challenges, such as increased computational complexity and large data requirements. In the future, optimization methods may further combine with deep learning and artificial intelligence technologies to cope with more complex market conditions. Meanwhile, with the development of quantum computing technology, new optimization algorithms may emerge in this field, further improving the efficiency and accuracy of option pricing. Overall, the application of optimization techniques not only advances classic option pricing theory but also provides more reliable support for risk management and investment decision-making in modern financial markets.

3. Machine Learning Methods

In option pricing research, many scholars have explored the application of various machine learning methods, such as Support Vector Machines (SVM), Support Vector Regression (SVR), and Decision Trees, in option pricing. Traditional option pricing models, like the Black-Scholes model, often fail to capture nonlinear features and complex volatility in the market due to their overly simplified assumptions. To address this issue, methods such as Support Vector Machines (SVM) and Support Vector Regression (SVR) have gradually been applied to option pricing. Machine learning methods, with their excellent nonlinear modeling capabilities, show strong predictive power when handling high-volatility and nonlinear market data.

The advantage of machine learning methods lies in their ability to automatically learn patterns from historical data without relying on assumptions, thus providing more accurate pricing. Additionally, machine learning methods can handle large-scale and high-dimensional data, continuously improving pricing accuracy through optimization algorithms. As a result, an increasing number of studies focus on how to integrate these methods with option pricing models to improve the predictive performance of classical models, especially in high-volatility and uncertain market conditions.

(Guidolin & Timmermann, 2003) studied option prices within the Bayesian learning framework, particularly the dynamics of implied volatility and changes in predictive density. The paper suggests that Bayesian learning methods can effectively integrate market information to dynamically adjust implied volatility in option pricing models. By introducing Bayesian inference, the study can predict the future trend of option prices and analyze their performance under different market conditions. The authors used an implied volatility model combined with Bayesian learning theory to model the predictive density of options. The experimental results show that Bayesian methods can better capture market uncertainty compared to traditional models, providing more accurate option pricing and predictive density, especially during periods of high market volatility. The paper also discusses the advantages and limitations of this method and highlights the potential of Bayesian learning in financial markets, particularly in handling complex and incomplete information.

(Park et al., 2014) compared parametric models and non-parametric machine learning models in the pricing of KOSPI 200 index options. The paper compares traditional parametric models, such as the Black-Scholes model, with non-parametric machine learning models like Support Vector Machines (SVM), exploring their application in option pricing. The experimental results show that non-parametric models exhibited higher accuracy in option pricing, especially under high market volatility. The study emphasizes the potential of machine learning methods in complex financial markets and provides theoretical support for future model selection in option pricing.

(Madhu et al., 2019) compared the performance of different kernel functions in Support Vector Regression (SVR) for option pricing. The paper explores various SVR kernel functions, such as linear, radial basis function (RBF), and polynomial kernels, and analyzes their advantages and limitations in option pricing. The experimental results indicate that the radial basis function (RBF) kernel performed the best in option price prediction, as it effectively captured nonlinear data patterns, providing accurate predictions. This study provides theoretical guidance for selecting option pricing models, particularly highlighting the application of SVR in complex financial markets.

(Ivaşcu, 2021) explored the use of machine learning methods for option pricing. The paper introduces different machine learning algorithms (such as Support Vector Machines, Decision Trees, Neural Networks, etc.) in option pricing. Through comparisons of various machine learning models, the authors found that machine learning methods could effectively capture the complex nonlinear relationships

in option pricing, especially under volatile market conditions. The study shows that machine learning methods not only outperform the classic Black-Scholes model in terms of accuracy but also handle more complex financial data, such as high-dimensional data and heterogeneous market environments. This study provides a new approach to option pricing, especially in dynamic and changing market conditions.

(R. Zhou, 2022) proposed an option pricing method that integrates machine learning algorithms. The paper combines multiple machine learning techniques, such as Support Vector Machines (SVM) and Decision Trees, to construct a comprehensive option pricing model. This model effectively captures the nonlinear features of option prices, particularly when dealing with complex and dynamic market environments, and shows high predictive accuracy. The study indicates that the integration of machine learning algorithms in option pricing applications...

(Y. Li et al., 2022) compared Support Vector Machines (SVM) and Artificial Neural Networks (ANN) in option price prediction. The article analyzes the strengths and weaknesses of these two common machine learning methods in the context of option price prediction. The experimental results demonstrate that Artificial Neural Networks outperform Support Vector Machines in handling complex nonlinear relationships, providing more accurate predictions, especially in highly volatile markets. The study indicates that while SVM performs well in certain situations, ANN has greater flexibility and predictive power in option pricing, offering a more precise tool for the financial field.

In summary, the application of non-neural machine learning methods in option pricing has made significant progress. By comparing the performance of traditional models with machine learning models, research shows that methods such as Support Vector Machines and Support Vector Regression can effectively capture the nonlinear relationships in option pricing, particularly under conditions of high market volatility and complex data, exhibiting higher accuracy than classical methods. For instance, Support Vector Regression (SVR) performs better than traditional regression models in option pricing by capturing more detailed market information. Furthermore, combining multiple machine learning methods can overcome the limitations of individual approaches, further improving prediction accuracy.

However, the application of machine learning methods in option pricing also faces several challenges, including the large demand for training data and the lack of model interpretability. Despite these challenges, as technology continues to progress, future research in this area is likely to integrate various machine learning methods, particularly ensemble learning and deep learning technologies, to further enhance the accuracy and adaptability of option pricing. Additionally, as financial market data becomes increasingly complex, machine learning methods' advantages in handling large-scale and heterogeneous data will become more evident, providing more powerful tools for future option pricing.

4. Neural Network Models and Deep Learning

With the advancement of computational power and big data technology, the application of neural networks and deep learning models in option pricing has made significant progress. Compared to traditional option pricing methods, such as the Black-Scholes model, these models are better at handling the nonlinear relationships and complex dynamic changes in the market. Neural networks, particularly feedforward neural networks (FNN) and deep learning models (such as LSTM), have become important tools in the financial sector. These methods automatically learn patterns from historical data and not only predict option prices but also capture nonlinear features and complex volatility patterns in the market.

Especially under conditions of high volatility and market uncertainty, traditional analytical methods often fail to accurately capture price dynamics, whereas neural networks, with their flexible structures and powerful fitting capabilities, can provide more accurate pricing results. As deep learning technology continues to develop, neural network-based option pricing models have not only improved pricing accuracy but also adapted to more complex market conditions and the need for multi-asset option pricing.

Therefore, neural networks and deep learning models have become research hotspots in the field of option pricing, especially when addressing complex financial products and high-dimensional data. These methods demonstrate enormous potential and broad application prospects.

(Malliaris & Salchenberger, 1993) proposed a neural network-based option pricing model. The paper introduces how to use feedforward neural networks (FNN) to model option prices. Compared to the traditional Black-Scholes model, neural networks can handle more complex nonlinear relationships, especially in highly volatile markets, where neural networks can capture more information and provide more accurate predictions. The study used multiple historical option datasets for training and evaluated the model's performance through regression analysis. The experimental results show that the neural network model has high accuracy in option price prediction, especially in complex market environments, outperforming traditional methods. However, the article also points out that the training process of neural network models is time-consuming and computationally demanding, especially with large-scale datasets, where training speed can become a bottleneck. This paper provides important theoretical support for the application of neural networks in the financial field, particularly in option pricing, showcasing their stronger adaptability and potential compared to traditional methods.

(Hutchinson et al., 1994) proposed a nonparametric method for pricing and hedging derivative securities through Learning Networks. The authors explore how neural network models can be used for nonparametric estimation of derivative securities, avoiding the reliance on parameters in traditional models. Through theoretical analysis and empirical research, the paper demonstrates the effectiveness of Learning Networks in financial...

(Anders et al., 1998) adopted neural networks to improve the accuracy of option pricing. The paper demonstrates how neural network models can capture the nonlinear relationships in option prices, thereby enhancing traditional pricing methods. By comparing traditional regression models, the study shows that neural networks provide more precise predictions, particularly when market uncertainty is high. This research offers a case study of neural networks in option pricing and highlights their potential in handling complex financial problems.

(Yao et al., 2000) explored the use of neural networks for option price prediction. The article suggests that neural

network models can capture the complex nonlinear relationships in option prices, showing greater flexibility and accuracy compared to traditional linear regression models. The research validated the effectiveness of neural networks in option pricing through training and testing on multiple option datasets, especially in volatile or complex market environments. The authors employed multilayer feedforward neural networks, adjusting weights and biases through optimization algorithms, significantly improving the prediction accuracy of option prices. Experimental results indicate that neural networks not only improve the predictive performance of traditional pricing models but also exhibit strong generalization ability, adapting to changing market conditions. However, the paper also points out that while neural networks perform excellently, they require a large amount of historical data for training, and the model's computational complexity is relatively high.

(Amilon, 2003) compared neural networks with the Black-Scholes model in option pricing and hedging. The paper suggests that although the Black-Scholes model is a traditional option pricing tool, neural networks demonstrate greater flexibility and precision in handling nonlinear relationships and complex market conditions. By comparing the pricing and hedging results of both methods, the authors found that neural networks were better at capturing market dynamics, particularly in highly volatile situations, outperforming the Black-Scholes model. The paper further analyzes the advantages of neural networks in option pricing and hedging, especially in the context of multidimensional input data and complex market environments. The study shows that neural network models outperform traditional Black-Scholes methods in terms of accuracy and adaptability but require more computational resources and training data.

(Bennell & Sutcliffe, 2004) compared the Black-Scholes model with artificial neural networks in pricing FTSE 100 options. The authors found that while the Black-Scholes model remains a traditional option pricing tool, neural networks are better at handling the nonlinear characteristics of market data, particularly when volatility is high. Neural networks showed higher accuracy and flexibility, even though their computational complexity is greater. Nonetheless, the advantages of neural networks in dealing with complex option pricing problems cannot be overlooked.

(Zhang & Lin, 2007) proposed a wavelet neural network-based option pricing model. The paper combines the advantages of wavelet analysis and neural networks to create a new option pricing method. The wavelet neural network, by integrating wavelet transform with neural networks, can effectively handle the nonlinearity and complexity in option pricing. The study shows that this model can better fit actual market data compared to the traditional Black-Scholes model, especially when there are jumps or sudden events in the market, exhibiting strong robustness and accuracy.

(Tan, 2008) proposed an option pricing method for the S&P 500 index based on BP neural networks. The paper combines BP neural networks with option pricing theory to study the pricing of S&P 500 index options. By training on historical data, the BP neural network can effectively capture the nonlinear relationships in option prices, providing precise pricing results. The research shows that this method can overcome the limitations of traditional models in handling complex option pricing problems, particularly in volatile markets, where BP neural networks exhibit strong adaptability and predictive capabilities.

(Gradojevic et al., 2009) proposed a modular neural network-based option pricing method. The article splits the neural network into several modules, each responsible for a different part of option pricing, providing a more efficient model architecture. With modular design, neural networks can better adapt to different market conditions when handling complex nonlinear option pricing problems. Experimental results show that this modular approach offers advantages in both computational efficiency and accuracy compared to traditional neural network methods, especially when pricing multiple option products, providing more accurate results. This research provides a new approach...

(Dong et al., 2013) proposed an option pricing model based on BP neural networks. The article applies BP neural networks to predict option prices, avoiding the dependence of traditional pricing models on market assumptions. Experimental results show that BP neural networks can predict option prices accurately by training on historical option data and automatically adjusting weights. This method exhibits strong accuracy and flexibility when handling complex financial data. The research suggests that neural network methods can provide a more dynamic solution for option pricing, particularly in high-volatility markets, where it holds significant application value.

(Yang et al., 2017) proposed an option pricing method based on gated neural networks, aiming to improve the model's performance through rational design. The article introduces a gating mechanism to control the network's state transition, ensuring the model better captures key features in market data. The research indicates that gated neural networks, by overcoming the shortcomings of traditional methods through rational design, enhance the model's generalization ability and predictive accuracy, especially in complex market environments.

(Xie & You, 2018) proposed a deep learning-based European stock index option pricing method, applied to the 50ETF options market. The article uses deep learning algorithms for stock index option pricing, where deep neural networks, trained on historical data, effectively capture the nonlinear features of option prices, providing more accurate pricing results than traditional models. The study shows that this method can maintain high predictive accuracy even in the face of high market volatility, demonstrating the potential of deep learning in the financial options market.

(Huh, 2019) proposed using exponential Lévy neural networks for option pricing. By combining Lévy processes with neural networks, the paper constructs a new option pricing model that effectively handles jumps and fat-tailed distributions that appear in financial markets. The research shows that exponential Lévy neural networks can capture market nonlinearities more accurately than the traditional Black-Scholes model, especially under high volatility and uncertainty, performing superiorly. This method provides a new theoretical framework for option pricing, particularly suitable for pricing complex financial products.

(L. Wang & Li, 2020) proposed a neural network-based option pricing method for the Shanghai Stock Exchange 50 ETF. The article models the options market using neural networks and trains on historical data, allowing it to better capture nonlinear and complex relationships in the market. Experiments demonstrate that the neural network model outperforms the traditional Black-Scholes model in option pricing, especially in handling high volatility and market uncertainty, providing more accurate predictions. This

research offers an effective alternative method for ETF option pricing, showcasing the broad application potential of deep learning technology in financial markets.

(Gonon & Schwab, 2021) explored the option pricing capability of deep ReLU networks in high-dimensional, exponential Lévy models. The article analyzes the expressive power of ReLU networks in complex financial models, noting that the network can effectively capture the complex relationships in high-dimensional market data, providing accurate predictions for option pricing. The research shows that deep neural networks, when dealing with high-dimensional and complex option pricing problems, have significant advantages over traditional methods, especially in high-dimensional datasets.

(F. Li, 2021) studied a deep learning-based numerical algorithm for basket option pricing. The article presents a deep learning method to tackle the pricing of basket options, using deep neural networks to fit complex option pricing functions. Experimental results show that deep learning methods better capture the nonlinear relationships in option prices, especially in multi-asset and complex market conditions, offering higher pricing accuracy compared to traditional methods. This study provides new insights into basket option pricing and demonstrates the application potential of deep learning in financial engineering.

(Sun et al., 2021) studied option pricing based on deep learning algorithms with a behavioral finance approach. The article combines deep learning with behavioral finance theory, proposing a new option pricing method aimed at capturing market participants' behavioral biases. By applying deep neural networks to train on market data, the model can better simulate market irrational behavior, thereby improving option pricing accuracy. Experimental results show that deep learning methods can effectively address behavioral option pricing, particularly in markets influenced by psychological factors and irrational volatility, demonstrating advantages over traditional methods.

(Song & Hou, 2021) proposed a neural network-based American option pricing method, applicable to the Black-Scholes model. The article uses neural network algorithms to price American options, solving the computational complexity issue encountered in traditional methods when pricing American options. Experimental results show that neural networks can effectively capture the nonlinear characteristics of options, especially when dealing with the early exercise problem of American options, providing more precise pricing than traditional models. This research offers a new technical approach for option pricing, showcasing the potential of neural networks in the complex option pricing domain.

(İltüzer, 2022) compared the performance of neural networks and the Black-Scholes model in BIST 30 index option pricing, particularly under different volatility forecasting methods. The article compares various volatility forecasting methods, including historical volatility and implied volatility, analyzing the advantages and disadvantages of neural networks and the Black-Scholes model in option pricing. Experimental results show that neural networks, especially under conditions of high market volatility, have advantages over the Black-Scholes model, providing more accurate pricing. This study demonstrates the application of neural networks in option pricing, particularly in dynamic market environments.

(Zhao et al., 2022) studied an LSTM (Long Short-Term Memory) based option pricing model for the CSI 300 ETF. The article leverages the time series modeling capability of LSTM, considering the temporal dependencies in market data, and proposes a pricing method for ETF options. Through empirical analysis of CSI 300 ETF options, the authors found that the LSTM model can effectively capture market dynamics, improving the accuracy of option price predictions. This research provides a new perspective on option pricing, especially in situations where financial market data has temporal dependencies.

(Anderson & Ulrych, 2023) proposed an accelerated American option pricing method that combines deep neural network technology to improve pricing efficiency and accuracy. The article compares traditional numerical methods with deep learning models and finds that neural networks can more effectively handle complex American option pricing problems, particularly in high-dimensional data and large sample sizes. The research shows that deep learning methods not only accelerate the pricing process but also significantly improve pricing accuracy, especially when market conditions change rapidly, demonstrating a clear advantage.

(Liu & Ma, 2023) proposed a BP neural network option pricing method optimized by simulated annealing. The article combines the global optimization capability of the simulated annealing algorithm with the powerful nonlinear fitting ability of BP neural networks to optimize the option pricing model. By optimizing the weights and biases of the BP neural network with simulated annealing, the method overcomes the issue of BP neural networks getting stuck in local optima. Experimental results show that this method outperforms traditional BP neural networks in terms of pricing accuracy and stability, especially when dealing with complex option pricing problems.

(Zhang & Zhou, 2023) studied a deep learning-based option price prediction method. The article applies deep learning techniques to predict option prices, training deep neural networks on historical data to forecast future price trends. The research shows that deep learning methods have strong accuracy in option price prediction, especially in volatile markets, capturing price fluctuations better than traditional pricing methods. This study demonstrates the application potential of deep learning in financial market forecasting and provides new technical support for option pricing and risk management.

(N. Zhang et al., 2023) studied basket option pricing based on deep learning methods. The article proposes a deep neural network model to address the pricing problem of multi-asset options. Through the deep learning model, it can more accurately capture the correlations between multiple assets and their impact on option prices. Experimental results show that this method provides higher prediction accuracy for basket option pricing than traditional models, particularly in handling the complex interactions of multiple assets. This research offers a new solution for basket option pricing and demonstrates the application potential of deep learning in pricing complex financial products.

(Z. Zhou et al., 2024) proposed a three-layer artificial neural network model for pricing multi-asset European options. The article introduces how a three-layer neural network structure can handle the complex option pricing problem involving multiple assets. By comparing with traditional pricing methods, experimental results show that the three-layer neural network can better capture the correlations and nonlinear features between assets, providing

more accurate predictions. This research not only highlights the advantages of neural networks in multi-asset option pricing but also emphasizes their potential in high-dimensional data and complex market conditions.

(Gan & Liu, 2024) introduced an option pricing method based on residual neural networks. The article incorporates residual neural networks (ResNet) to overcome some of the shortcomings of traditional neural networks in option pricing, particularly overfitting and insufficient training. The study found that residual neural networks can effectively extract complex features from market data, improving the accuracy and efficiency of pricing, especially when handling datasets with high-dimensional features, demonstrating strong performance.

In summary, the application of neural networks and deep learning models in option pricing has become an important direction in modern financial modeling. By introducing neural networks, especially feedforward neural networks and LSTM, researchers can handle more complex nonlinear relationships and time series data, making option pricing not only more accurate but also more adaptive. Many studies show that neural network models can provide more accurate option price predictions compared to traditional methods, especially in volatile and uncertain markets. For example, deep learning models in multi-asset options and basket options can capture correlations between assets and improve pricing accuracy.

However, despite the great potential of neural networks in option pricing, they also face challenges such as high computational resource demands and long model training times. Future research may focus more on optimizing these models to handle large-scale datasets more efficiently, especially in high-frequency trading and complex derivative pricing areas. Additionally, combining reinforcement learning and other machine learning methods to further enhance the performance and market adaptability of option pricing models will likely become a key focus in future research.

Overall, neural networks and deep learning methods have brought revolutionary improvements to option pricing, not only enhancing pricing accuracy but also providing new solutions for handling option pricing problems under dynamic and complex market conditions. As technology continues to develop, these methods are expected to play an increasingly important role in financial markets.

5. Hybrid Models

In recent years, research in the field of option pricing has gradually shifted toward hybrid methods that combine multiple models to overcome the limitations of individual models and improve pricing accuracy. Traditional option pricing models, such as the Black-Scholes model, perform excellently in many financial markets, but often fail to provide accurate predictions in the face of high volatility, nonlinearity, and complex market conditions. To address these issues, scholars have proposed various hybrid methods that combine traditional models with emerging technologies such as machine learning, deep learning, and optimization algorithms. By optimizing the model training process and improving the model's adaptability, these methods achieve more precise option pricing.

An important characteristic of hybrid methods is that they combine the advantages of different approaches to compensate for each other's shortcomings. For example, combining genetic algorithms with neural networks to perform global optimization of the neural network can improve both the prediction accuracy and computational efficiency of option pricing models. Furthermore, combining deep learning with fuzzy logic, particle swarm optimization, and other methods allows for the handling of more complex nonlinear and high-dimensional data, adapting to dynamic market changes. Through these innovative hybrid models, option pricing becomes not only more accurate but also capable of addressing increasingly complex and variable market conditions, driving the further development of option pricing methods.

(P. R. Lajbcygier & Connor, 1997) proposed an improved option pricing method that combines artificial neural networks and the bootstrap method. The article demonstrates that by using a neural network model for option pricing predictions and enhancing the model using the bootstrap method, the accuracy and robustness of pricing can be effectively improved. Experimental results show that this method significantly enhances prediction accuracy, particularly in high-volatility market conditions, with the combination of neural networks and the bootstrap method demonstrating strong adaptability and stability. This research offers a new solution for option pricing, especially when dealing with complex and incomplete information.

(P. Lajbcygier, 2004) introduced an improved option pricing method that incorporates product constraints into hybrid neural networks. The author improved the structure of neural networks by introducing product constraints, thereby enhancing the accuracy and stability of option pricing. This method optimizes traditional neural networks and adapts to the diversity of option pricing in financial markets, particularly in highly volatile market conditions, demonstrating stronger robustness and accuracy.

(Zhang & Lin, 2009) proposed an option price prediction model that applies hybrid neural networks and genetic algorithms. The article combines the nonlinear fitting ability of neural networks with the global optimization characteristics of genetic algorithms, optimizing the training process of neural networks through genetic algorithms. Experimental results show that the hybrid model provides higher prediction accuracy in option pricing, especially in highly volatile markets, demonstrating better adaptability and robustness than traditional models. This research offers an innovative hybrid model for option pricing, combining the advantages of intelligent optimization technologies and deep learning.

(Liang et al., 2009) combined neural networks with support vector regression (SVR) to improve option price prediction accuracy. The article combines these two machine learning methods to overcome the limitations of individual methods and enhance the precision of the predictions. Experimental results show that the model combining neural networks and SVR significantly outperforms the individual neural network and SVR models in option pricing, particularly when dealing with complex market data, demonstrating stronger robustness and adaptability. This research provides an effective machine learning hybrid method for option pricing, helping to improve prediction accuracy.

(Y.-H. Wang, 2009) proposed a stock index option price prediction model based on nonlinear neural networks, combined with the hybrid GJR-GARCH method. The article points out that while traditional GARCH models can capture market volatility, they have certain limitations in handling nonlinear relationships. By incorporating neural networks and

taking advantage of the GJR-GARCH model, the hybrid model can better predict option prices, especially in high-volatility markets. The study shows that the hybrid model significantly improves accuracy and stability compared to traditional methods.

(Cai & Kou, 2011) proposed a mixed-exponential jump diffusion model for option pricing. The article combines exponential jump diffusion processes with mixed distributions to account for jump phenomena in financial markets, which cannot be adequately captured by traditional Brownian motion models. Using this model, the author can handle asymmetric jump conditions in the market, offering a more accurate representation of the underlying processes.

(Jang & Lee, 2019) proposed a generative Bayesian neural network model for risk-neutral pricing of American index options. The article utilizes Bayesian methods to generatively model the neural network, capturing the uncertainty in option pricing, especially under complex market conditions. Through generative modeling, the authors are able to more accurately estimate the risk-neutral pricing of options and handle the early exercise feature of American options. Experimental results demonstrate that this model outperforms traditional pricing methods, particularly in predicting option prices and determining optimal exercise strategies, with higher accuracy and robustness. This research provides an innovative solution for the pricing of American options.

(Arin & Ozbayoglu, 2022) proposed a hybrid computational intelligence model based on deep learning for option pricing. The article combines deep neural networks with other computational intelligence techniques such as fuzzy logic and genetic algorithms to create a multi-level hybrid model. Through empirical analysis of different option products, the study shows that the hybrid model outperforms traditional models in both pricing accuracy and computational efficiency. Particularly when dealing with nonlinear and high-dimensional market data, deep learning methods provide more precise pricing results. This research offers an innovative framework for option pricing, highlighting the potential and application value of deep learning in the financial field.

(Qian et al., 2022) proposed an option pricing method based on a genetic algorithm and BP neural network (GA-BP). The article combines genetic algorithms with BP neural networks to optimize the training process of the network, addressing the slow convergence and local optimal issues inherent in traditional BP neural networks for option pricing. Experimental results show that the GA-BP neural network model has better prediction accuracy, especially when handling nonlinear and complex option pricing problems, and has a clear advantage over traditional methods. This research provides a new optimization approach for option pricing, demonstrating the effectiveness of genetic algorithms in neural network training.

(Gatta et al., 2023) explores the application of a physics-informed neural network (PINN) based meshless method for pricing American options. The article introduces a meshless method that combines physical laws with market data, using neural networks to efficiently price options. The study demonstrates that PINNs, by merging physical knowledge and data-driven methods, provide more accurate and computationally efficient results compared to traditional methods in solving complex option pricing problems.

(W. Zhang et al., 2024) proposed an LSTM hybrid neural network option pricing model based on an improved particle swarm optimization (PSO) algorithm. The article combines the global optimization capability of PSO with the time-series processing ability of LSTM networks to create a new option pricing model. By improving the PSO algorithm, the training process of the LSTM neural network is optimized, enhancing the accuracy of option pricing. Experimental results show that the hybrid model provides more precise option pricing, especially under high volatility and nonlinear conditions in complex financial market environments. This research demonstrates the huge potential of combining PSO and LSTM in financial modeling.

(Shvimer & Zhu, 2024) proposed a new hybrid neural network model for option pricing. The model combines different types of neural networks, using multi-level information fusion to improve option pricing accuracy. The study shows that this hybrid neural network outperforms traditional methods in terms of computational efficiency and predictive accuracy, especially when applied to large-scale market data.

In summary, hybrid methods have demonstrated tremendous potential and innovation in option pricing. By combining different optimization algorithms and machine learning techniques, researchers have effectively improved the accuracy of option pricing, especially under high volatility, nonlinear, and complex market conditions. For instance, hybrid models that combine genetic algorithms with neural networks can optimize the network training process, avoiding local optimal problems and improving the stability of pricing results. Meanwhile, the combination of particle swarm optimization and LSTM provides new solutions for time-series data option pricing, demonstrating strong adaptability in dynamic markets.

Despite the significant progress made in the application of hybrid methods in option pricing, challenges such as high computational resource requirements and complex model training still remain. Future research may further optimize these hybrid models by incorporating more advanced technologies such as reinforcement learning and adaptive algorithms, to improve the efficiency and accuracy of option pricing. Additionally, with the continuous development of financial markets, hybrid methods may demonstrate even greater potential in areas such as pricing more complex financial derivatives and cross-asset options.

In conclusion, hybrid methods not only provide new solutions for option pricing but also inject new momentum into the field of financial modeling. With the ongoing advancement of computational technologies and financial theories, the research and application of hybrid models will further drive innovation in financial engineering and risk management.

6. Conclusion and Outlook

This review systematically summarizes the research progress based on optimization methods, machine learning approaches, and neural network models, while analyzing the advantages and challenges of combining multiple models.

First, research based on optimization methods indicates that by combining modern optimization techniques such as genetic algorithms and particle swarm optimization, classical option pricing models can overcome the limitations of traditional assumptions and better adapt to complex market conditions. These methods not only improve pricing accuracy but also expand the applicability of the models, providing new tools for risk management in the options market. Secondly,

the introduction of machine learning methods has further enriched the selection of option pricing models. Models like support vector machines and decision trees can efficiently handle nonlinear data, especially excelling in high-dimensional data modeling. Additionally, neural networks and deep learning technologies, with their powerful feature extraction and nonlinear fitting capabilities, have become research hotspots in the field of option pricing. Studies have shown that deep learning models have significant advantages in complex option pricing and high-dimensional data modeling.

However, existing research also faces some challenges. For example, complex models demand high computational resources, and the training process heavily depends on large-scale high-quality data. Moreover, the interpretability of machine learning models limits their widespread adoption in practical markets. Future research can be directed toward the following areas:

Incorporating more cutting-edge technologies: Such as reinforcement learning, adaptive optimization algorithms, and quantum computing, to further improve the efficiency and accuracy of option pricing models.

Enhancing model interpretability: Developing transparent model structures and visualization tools to enhance the trust and understanding of financial practitioners.

Expanding application scenarios: Exploring the potential of hybrid models in complex derivatives, cross-asset pricing, and high-frequency trading.

Strengthening data fusion and dynamic modeling: Fully utilizing multi-source heterogeneous data (e.g., macroeconomic data, market sentiment data, etc.) to develop more robust dynamic pricing models.

Overall, the application of machine learning techniques in option pricing holds great potential. With the continuous advancement of computational power and algorithm design, these technologies will be more widely applied in financial markets in the future, not only driving innovation in option pricing models but also providing more scientific support for risk management and investment decision-making.

References

[1] Amilon, H. (2003). A neural network versus black–scholes: A comparison of pricing and hedging performances. Journal of Forecasting, 22(4), 317–335.

[2] Anders, U., Korn, O., & Schmitt, C. (1998). Improving the pricing of options: A neural network approach. Journal of Forecasting, 17(5-6), 369–388.

[3] Anderson, D., & Ulrych, U. (2023). Accelerated american option pricing with deep neural networks. Quantitative Finance and Economics, 7(2), 207–228.

[4] Andreou, P. C., Charalambous, C., & Martzoukos, S. H. (2008). Pricing and trading european options by combining artificial neural networks and parametric models with implied parameters. European Journal of Operational Research, 185(3), 1415–1433.

[5] Arin, E., & Ozbayoglu, A. M. (2022). Deep learning based hybrid computational intelligence models for options pricing. Computational Economics, 59(1), 39–58.

[6] Bennell, J., & Sutcliffe, C. (2004). Black–scholes versus artificial neural networks in pricing FTSE 100 options. Intelligent Systems in Accounting, Finance & Management: International Journal, 12(4), 243–260.

[7] Benth, F. E., Detering, N., & Galimberti, L. (2024). Pricing options on flow forwards by neural networks in a hilbert space. Finance and Stochastics, 28(1), 81–121.

[8] Cai, N., & Kou, S. G. (2011). Option pricing under a mixed-exponential jump diffusion model. Management Science, 57(11), 2067–2081.

[9] Das, S. P., & Padhy, S. (2017). A new hybrid parametric and machine learning model with homogeneity hint for european-style index option pricing. Neural Computing and Applications, 28, 4061–4077.

[10] Dong, Y., Wuriga, & Qi, S. (2013). Option pricing model based on BP neural network. Journal of Ludong University (Natural Science Edition), 29(03), 196–199.

[11] Eskiizmirliler, S., Günel, K., & Polat, R. (2021). On the solution of the black–scholes equation using feed-forward neural networks. Computational Economics, 58, 915–941.

[12] Gan, L., & Liu, W. (2024). Option pricing based on the residual neural network. Computational Economics, 63(4), 1327–1347.

[13] Gatta, F., Di Cola, V. S., Giampaolo, F., Piccialli, F., & Cuomo, S. (2023). Meshless methods for american option pricing through physics-informed neural networks. Engineering Analysis with Boundary Elements, 151, 68–82.

[14] Gonon, L., & Schwab, C. (2021). Deep ReLU network expression rates for option prices in high-dimensional, exponential lévy models. Finance and Stochastics, 25(4), 615–657.

[15] Gradojevic, N., Gençay, R., & Kukolj, D. (2009). Option pricing with modular neural networks. IEEE Transactions on Neural Networks, 20(4), 626–637.

[16] Guidolin, M., & Timmermann, A. (2003). Option prices under bayesian learning: Implied volatility dynamics and predictive densities. Journal of Economic Dynamics and Control, 27(5), 717–769.

[17] Guo, H. (2016). Numerical solution of the optimized black-scholes option pricing model based on neural networks. Journal of Harbin Normal University (Natural Science Edition), 32(04), 41–44.

[18] Hainaut, D., & Casas, A. (2024). Option pricing in the heston model with physics inspired neural networks. Annals of Finance, 20(3), 353–376.

[19] Huh, J. (2019). Pricing options with exponential lévy neural network. Expert Systems with Applications, 127, 128–140.

[20] Hutchinson, J. M., Lo, A. W., & Poggio, T. (1994). A nonparametric approach to pricing and hedging derivative securities via learning networks. The Journal of Finance, 49(3), 851–889.

[21] İltüzer, Z. (2022). Option pricing with neural networks vs. Black-scholes under different volatility forecasting approaches for BIST 30 index options. Borsa Istanbul Review, 22(4), 725–742.

[22] Ivaşcu, C.-F. (2021). Option pricing using machine learning. Expert Systems with Applications, 163, 113799.

[23] Jang, H., & Lee, J. (2019). Generative bayesian neural network model for risk-neutral pricing of american index options. Quantitative Finance, 19(4), 587–603.

[24] Lajbcygier, P. (2004). Improving option pricing with the product constrained hybrid neural network. IEEE Transactions on Neural Networks, 15(2), 465–476.

[25] Lajbcygier, P. R., & Connor, J. T. (1997). Improved option pricing using artificial neural networks and bootstrap methods. International Journal of Neural Systems, 8(04), 457–471.

[26] Li, F. (2021). Numerical algorithm for basket option pricing based on deep learning. Journal of Shandong University of Technology (Natural Science Edition), 35(02), 38–42. https://doi.org/10.13367/j.cnki.sdgc.2021.02.008

[27] Li, Y., Liu, L., & Lü, H. (2022). A comparative study of support vector machines and artificial neural networks in option price prediction. Journal of Xichang University (Natural Science Edition), 36(02), 31–36. https://doi.org/10.16104/j.issn.1673-1891.2022.02.007

[28] Liang, X., Zhang, H., Xiao, J., & Chen, Y. (2009). Improving option price forecasts with neural networks and support vector regressions. Neurocomputing, 72(13-15), 3055–3065.

[29] Liu, X., & Ma, Y. (2023). Research on option pricing based on BP neural network optimized by simulated annealing algorithm (pp. 386–399). Zhengzhou University International School; Zhengzhou University Henan Big Data Research Institute.

[30] Madhu, B., Paul, A. K., & Roy, R. (2019). Performance comparison of various kernels of support vector regression for predicting option price. International Journal of Discrete Mathematics, 4, 21–31.

[31] Malliaris, M., & Salchenberger, L. (1993). A neural network model for estimating option prices. Applied Intelligence, 3, 193–206.

[32] Mehrdoust, F. (2024). Calibration of european option pricing model in uncertain environment using an artificial neural network. Available at SSRN.

[33] Moreno T, J. F., Zapata, C., & Aragon, D. (2024). Neural networks and the nonlinear feynman–kac theorem applied to financial options pricing. SN Computer Science, 5(6), 697.

[34] Park, H., Kim, N., & Lee, J. (2014). Parametric models and non-parametric machine learning models for predicting option prices: Empirical comparison study over KOSPI 200 index options. Expert Systems with Applications, 41(11), 5227–5237.

[35] Qian, L., Zhao, J., & Ma, Y. (2022). Option pricing based on GA-BP neural network. Procedia Computer Science, 199, 1340–1354.

[36] Santos, D. de S., & Ferreira, T. A. E. (2024). Neural network learning of black-scholes equation for option pricing. arXiv Preprint arXiv:2405.05780.

[37] Shvimer, Y., & Zhu, S.-P. (2024). Pricing options with a new hybrid neural network model. Expert Systems with Applications, 251, 123979.

[38] Song, H., & Hou, D. (2021). Neural network algorithm for american option pricing under the black-scholes model. Journal of Jilin University (Science Edition), 59(05), 1089–1092. https://doi.org/10.13413/j.cnki.jdxblxb.2021197

[39] Sun, Y., Qiu, Z., Yao, Y., & Liu, C. (2021). Behavioral option pricing based on deep learning algorithm. Journal of Systems Management, 30(04), 697–708.

[40] Tan, D. (2008). S&p 500 index option pricing based on BP neural network. Statistics and Information Forum, 11, 40–43.

[41] Wang, L., & Li, Y. (2020). Option pricing of SSE 50ETF based on neural networks. Computer Knowledge and Technology, 16(01), 196–198. https://doi.org/10.14004/j.cnki.ckt.2020.0086

[42] Wang, Y.-H. (2009). Nonlinear neural network forecasting model for stock index option price: Hybrid GJR–GARCH approach. Expert Systems with Applications, 36(1), 564–570.

[43] Xie, H., & You, T. (2018). Research on european stock index option pricing based on deep learning algorithm: Evidence from the 50ETF option market. Statistics and Information Forum, 33(06), 99–106.

[44] Yang, Y., Zheng, Y., & Hospedales, T. (2017). Gated neural networks for option pricing: Rationality by design. Proceedings of the AAAI Conference on Artificial Intelligence, 31.

[45] Yao, J., Li, Y., & Tan, C. L. (2000). Option price forecasting using neural networks. Omega, 28(4), 455–466.

[46] Zhang, H., & Lin, H. (2007). Option pricing model based on wavelet neural networks. Journal of Southeast University (Natural Science Edition), 04, 716–720.

[47] Zhang, H., & Lin, H. (2009). Option price prediction model using hybrid neural networks and genetic algorithms. Journal of Industrial Engineering and Engineering Management, 23(01), 59–62+87.

[48] Zhang, H., & Zhou, W. (2023). Research on option price prediction based on deep learning. Business Exhibition Economy, 11, 98–101. https://doi.org/10.19995/j.cnki.CN10-1617/F7.2023.11.098

[49] Zhang, L., & Zhang, W. (2018). Research on hybrid neural network option pricing based on heston model and genetic algorithm optimization. Journal of Industrial Engineering and Engineering Management, 32(03), 142–149. https://doi.org/10.13587/j.cnki.jieem.2018.03.017

[50] Zhang, N., Tu, Y., Zheng, Y., & Chen, M. (2023). Deep learning method for basket option pricing. Journal of Central University of Finance and Economics, 05, 50–62. https://doi.org/10.19681/j.cnki.jcufe.2023.05.009

[51] Zhang, W., Gong, W., & Hu, W. (2024). Option pricing model based on LSTM hybrid neural network with improved particle swarm optimization algorithm. Systems Engineering, 42(01), 139–148.

[52] Zhao, K., Zhang, J., & Zhu, Y. (2022). Research on option pricing model of CSI 300 ETF based on LSTM. Journal of Shanxi Normal University (Natural Science Edition), 36(03), 31–38. https://doi.org/10.16207/j.cnki.1009-4490.2022.03.001

[53] Zhou, R. (2022). Option pricing using integrated machine learning algorithms. Journal of Systems Management, 31(03), 476–485.

[54] Zhou, Z., Wu, H., Li, Y., Kang, C., & Wu, Y. (2024). Three-layer artificial neural network for pricing multi-asset european option. Mathematics, 12(17), 2770.