Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 6745980, 9 pages
https://doi.org/10.1155/2022/6745980

Research Article

Correlation Financial Option Pricing Model and Computer Simulation under a Stochastic Interest Rate

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Received 6 June 2022; Revised 6 July 2022; Accepted 19 July 2022; Published 10 August 2022

Academic Editor: Kapil Sharma

With the continuous expansion of the consumer interest rate market today, the risks brought by interest rate fluctuations have had a huge and far-reaching impact on the financial markets of many countries and it is becoming more and more important to simulate the pricing of financial options. In the traditional pricing model of financial options, the pricing standard of the pricing model is generally set as a financial product with random disturbance characteristics and the market price of its transaction does not follow the arbitrage principle of financial product pricing. It is easy to generate errors and cause risks, and the accuracy of traditional financial option pricing models is not high, and the simulation time is long, which greatly reduces the rate of financial transactions. To improve the accuracy of option pricing models, this paper uses computer simulation technology to simulate the pricing of correlated financial options under stochastic interest rates. From the four aspects of error, risk parameters, success rate, and simulation time, it is tested to observe the influence of computer simulation technology on the financial option pricing model. The final results show that by using computer simulation technology, the error of the correlation financial option pricing model under the random interest rate is reduced, the success rate is improved, the risk parameter is reduced by 3.03%, and the simulation time is reduced by 0.605 seconds.

1. Introduction

Option price is very important in option terms, and it will change as the contract terms change. Its speed of change directly affects the profit and loss of both buyers and sellers. Simulation of option pricing is an important issue in option trading. Uncertainty about the cost-effectiveness of options is a big problem for investors in the process of creating and developing global stock markets. The cost-effectiveness of options is one of the most important variables in the financial market, and its changes will have a great impact on the entire financial market and even the entire economic system. Using computer simulation technology to analyze the stochastic interest rate of the option pricing model can timely understand the change of the financial option price and carry out a reasonable price, which can avoid the occurrence of financial risks and promote the development of the financial industry.

Option pricing models are widely used in financial transactions, and more and more scholars are devoted to the study of option pricing models. Tomovski et al. evaluated the empirical performance of a calendar option pricing model with latent variables. The model uses the stochastic volatility formula, and through experiments, it is found that the values of the relative risk aversion coefficient and the intertemporal elasticity of substitution gradually decrease [1]. Tunaru and Zheng embed the Black-Scholes option pricing model in a quantum physical environment, resulting in a function. This function helps determine the existence of a "financial" state function. It has been experimentally demonstrated that the Black-Scholes model can be captured in a quantum physical environment, incorporating arbitrage in other arbitrage-free models in a natural way [2]. Gong and Zhuang investigated a method for pricing options in the context of a CEV model using Lie algebra techniques when model parameters are time dependent. The method can be easily extended to other alternative-valued models with clear algebraic systems. Further results can be generated using various functional forms of the rate and index text structures [3]. Dubinsky et al. proposed a fuzzy pricing model for the volatility (fuzzy volatility) in the binary tree option pricing model. By using the binomial pricing option model, more stocks can be obtained, thereby improving the accuracy of option pricing simulated in financial markets. Accurate option pricing can allow investors to avoid financial risks [4]. Orbay et al. researched and developed an option pricing model that incorporates randomly distributed option returns, which is used to simulate market option prices to assess the need for financial market risk. Experiments were conducted to evaluate the performance of the new model with experimental numerical simulations, and the final experimental results proved that the model performed better than other models [5]. Mollapourasl et al. proposed a coupled nonlinear volatility and option pricing model, which produces a leverage effect, that is, stock volatility is (negatively) correlated with stock returns, which can be seen as a coupled nonlinear wave alternative pricing model for Black-Scholes options [6]. Parker proposed a European option pricing model using an advanced model (MOR) approach. The European option pricing model based on the Black-Scholes equation is implemented using the FDM method, and the MOR model is at least 2 times faster than the original FDM model in terms of computational cost with negligible compromise in accuracy [7]. The above studies have shown the advantages of option pricing models, but with the emergence of new technologies, options pricing models also have new problems.

Computer simulation technology is one of the new technologies applied in most modern operating systems. Many scholars have done research on computer simulation technology. Atkinson et al. believed that computer simulation technology has become an important tool for structural analysis and design. Under the action of disaster loads such as explosion, penetration, collapse, or typhoon, the test method is difficult to analyze and the advantages of computer simulation method such as safety, high efficiency, and low cost are more obvious in these problems [8]. Straka et al. developed a new type of electromagnetic wave induction heating equipment XAEMH-1, using a computer simulation system to dynamically predict and evaluate the efficiency of this electromagnetic heating process. The effectiveness of the new technology is verified through experiments, and satisfactory results have been achieved [9]. Based on the existing research results and simulation cases, Niek et al. introduced the application and progress of computer simulation technology in structural seismic design, seismic evaluation of existing structures, structural response analysis under extreme external forces, seismic planning or evaluation of urban large-area systems, etc. [10]. In order to explore and evaluate the application of computer simulation technology combined with multimedia teaching in CPR training, Niek et al. conducted the CPR theory and skill tests on 62 emergency physicians. It was found that computer simulation technology combined with multimedia teaching has important application value in cardiopulmonary resuscitation training, which can significantly improve team work ability [11]. Wang et al. has found computer simulations to be an effective way to pretest proposed systems, programs, or policies before developing expensive prototypes, field testing, or actual implementation. In a simulation analysis, the computer tracks the implications and consequences of a proposed system or course of action in detail. Simulations are more realistic, easier to understand, and more conclusive than other forms of analysis [12]. In order to shorten the development cycle of new vehicles and reduce the manufacturing cost of prototype vehicles, Mrozek and Burczynski proposed a new simulation method to predict the use of various parts of the car body through computer simulation, which can search for the acceleration and dynamic response of a specific area and the corresponding energy density [13]. Song discussed the application and function of computer simulation technology in medical physics teaching and analyzed the necessity of computer simulation technology in medical physics teaching. According to the characteristics of the relevant teaching content, he expounded and explained the role and advantages of computer simulation technology through appropriate teaching examples [14]. Appeal research shows that computer simulation techniques have applications in various industries.

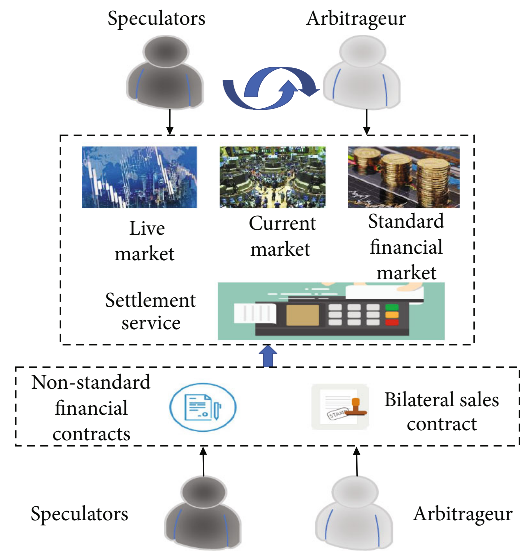

Figure 1: Financial option pricing models.

Computer simulation technology is a very active research field developed in recent years. Computer simulation technology has strong adaptability to solve all kinds of complex optimization problems. Using computer simulation technology to calculate the pricing of correlated financial options under random interest rates can avoid errors to the greatest extent and reduce risks. This paper applies the computational simulation technology to the financial option pricing model to increase the accuracy of option pricing and promote the development of the financial market.

2. Computer Simulation on the Financial Option Pricing Model

2.1. Financial Option Pricing Model. Computer simulation technology can be a flexible tool for financial market participants to avoid risk. If the right pricing model can be

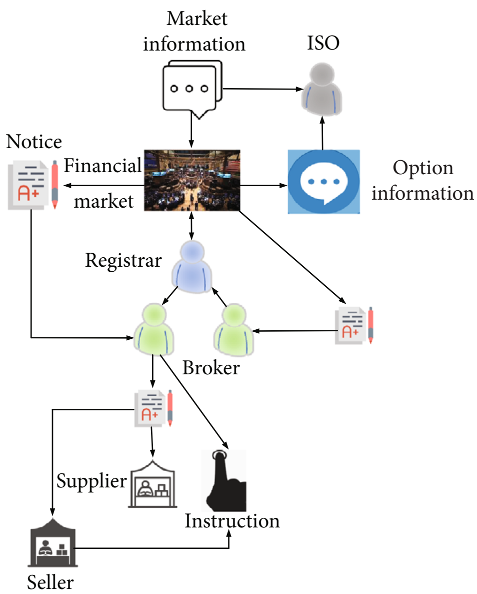

Figure 2: Option pricing transaction process.

combined with computer simulation technology, on the one hand, the advantages of stock options can be exerted, and on the other hand, the unstable changes of direct assets and the risks of market currency transactions can be avoided, allowing participants to complete transactions more smoothly. Due to the nonstorable characteristics of financial items, the system dispatch center must strictly control the transaction plan and repeatedly verify the security of the financial option pricing model system [15–17]. This requires a large amount of information exchange between the participants and the option pricing model, which increases the accuracy of option pricing to a certain extent and avoids risks [18]. Figure 1 presents a typical financial market including option pricing, which provides a reference for the design of the financial option market. Participating members can judge the future trend of financial option pricing based on the information obtained by computer simulation technology.

The scale of the market has multiple meanings, one refers to the size of the spot market, and the other refers to the size of the option market. The system includes a series of financial derivatives such as futures, options, and forward contracts, which involve not only financial transactions but also a large number of speculators and arbitrageurs using the leverage of options to gain profits in the market, greatly enhancing the liquidity and activity of the financial market.

2.2. Option Transaction Process. Financial market participants are mainly e-commerce sellers and e-commerce buyers, traders (risk), and arbitrageurs (buying multiple options at once to lock in risk opportunities) [19–21]. First, market participants send trade orders to the option pricing model system and instruct managing brokers in financial transactions to trade for them. Managing brokers submit trade orders to the authority for product prices, final prices, types of buy and sell contracts, and strike prices and receive comments on price order information. When participants receive all the information from the managing broker, all orders are bought and sold through the electronic trading system in accordance with the principle of "money and time first." An independent system administrator is responsible for accounting for system security data, and they need to ensure that the system is secure and stable [22, 23]. After the transaction is completed, the electronic trading system determines the price and volume of the transaction and feeds back the notification of the transaction option to the managing broker, which then sends it to the corresponding client, as shown in Figure 2.

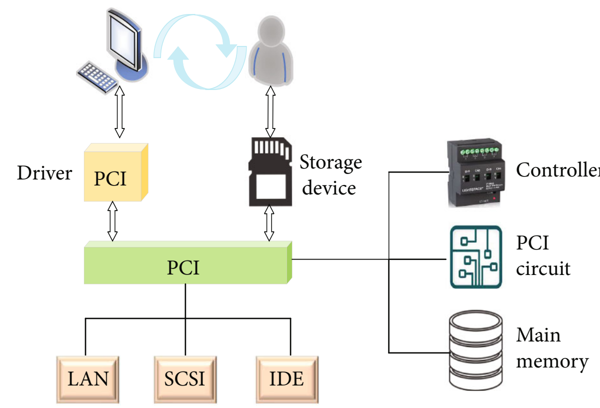

Figure 3: Computer simulation system structure diagram.

2.3. Computer Simulation System Structure. The option pricing model is studied using a computer simulation system. The computer simulator must have the following functions: the system controls the computer to set the program and transfer data to the infrared driver, collect information in frames from a special table, and send it to the crawler. The directional infrared tracker data and location information are then sent through the panel management applicant's job capture card. Frame information is returned to the desired information memory. It is then sent through the local channel to the product control computer for storage display and setting changes. Option information is stored and transmitted to a computer simulator. A computer simulator is a combination of a control panel and a special panel [24]. The main function of the control computer is to complete functions such as human-computer interaction, data storage, and scheduling, including device drivers, human-computer interaction interfaces, and storage devices, as shown in Figure 3.

Option pricing models require a computer simulation program to complete the application and software design. According to its structural characteristics, the design is divided into three parts. The first part mainly involves the design of option pricing and the drafting of device drivers. The bus of the model is a bus that is not connected to a specific processor; it can maintain high performance at high clock frequencies and support plug-and-play and any compatible card access system work. The second part is the design of the compatible card. One end of the compatible card is connected to the infrared controller through half-side serial communication, and the other end communicates with the company's control computer through the channel and control. The computer communicates with the infrared image via the researcher information bus. Compatible cards have good electrical insulation properties, thereby improving the anti-interference and security of the motherboard system. The third part realizes human-computer interaction through the human-computer interaction view processing the human-computer interaction interface design of the pop-up simulation program, exploring function definitions, state information provided by the main control, etc., so as to realize human-computer interaction [25].

2.4. Recommendation Algorithm

2.4.1. B-S Option Pricing Model. The model uses stochastic differential equations to describe the market fluctuation law of derivatives. According to this law, the current value of the derivative product is determined, which is the differential equation that the price of any derivative product without dividends paying the underlying asset must satisfy. By solving this equation, the B-S option pricing model finally obtains the pricing formulas for European call options and put options [26].

The value of the underlying asset is similar to the "Brownian motion," that is, the value of the underlying asset randomly follows the rate of change during the transfer. Therefore, regardless of the time period, the distribution of the value of the underlying assets is normal [27]. The variance of the underlying performance return does not change, and the background value of the underlying price S follows the following stochastic process:

$$dS = \mu S dt + \sigma S dq. \tag{1}$$

Among them, μ is the expected return of the underlying asset and σ is the volatility of the underlying asset price, both of which are constants. q is a variable of the Wiener process, that is, $dq = \varepsilon\sqrt{dt}$ obeys a standard normal distribution (that is, a normal distribution with a mean of 0 and a standard deviation of 1.0).

Let f be the price of the derivative security priced at S; then, f is some function of S and t. According to equation (1), we have the following:

$$df = \left(\frac{\partial f}{\partial S}\mu S + \frac{\partial f}{\partial t} + \frac{1}{2}\frac{\partial^2 f}{\partial S^2}\sigma^2 S^2\right)dt + \frac{\partial f}{\partial t}\sigma S dq. \tag{2}$$

Discrete equations (1) and (2), respectively, to get the following:

$$\Delta S = \mu S \Delta t + \mu S \Delta q, \tag{3}$$

$$\Delta f = \left(\frac{\partial f}{\partial S}\mu S + \frac{\partial f}{\partial t} + \frac{1}{2}\frac{\partial^2 f}{\partial S^2}\sigma^2 S^2\right)\Delta t + \frac{\partial f}{\partial t}\sigma S \Delta q. \tag{4}$$

The portfolio is now constructed as follows: −1 corresponds to derivative securities and $+(\partial f/\partial S)$ is the underlying asset.

That is, the number of derivative securities sold is 1 and the number of underlying assets purchased is $+(\partial f/\partial S)$. Definition $\mathfrak{I}$ represents the value of a portfolio of securities; then,

$$\mathfrak{I} = -f + \frac{\partial f}{\partial S}S. \tag{5}$$

After time Δt, the value of the portfolio changes to $\Delta\mathfrak{I}$ as follows:

$$\Delta\mathfrak{I} = -\Delta f + \frac{\partial f}{\partial S}\Delta S. \tag{6}$$

Substituting equations (3) and (4) into (6) yields the following:

$$\Delta\mathfrak{I} = \left(-\frac{\partial f}{\partial t} - \frac{1}{2}\frac{\partial^2}{S^2}\sigma^2 S^2\right)\Delta t. \tag{7}$$

This process does not include uncertainty Δz, so portfolio $\mathfrak{I}$ is obtained from Δt and does not create risk. The immediate rate of return on this portfolio is the short-term risk-free rate w. In any case,

$$\Delta\mathfrak{I} = w\mathfrak{I}\Delta t. \tag{8}$$

Combining equations (5) and (7) yields the following:

$$\left(\frac{\partial f}{\partial t} + \frac{1}{2}\frac{\partial^2 f}{\partial S^2}\right)\sigma^2 S^2 \Delta t = w\left(f - \frac{\partial f}{\partial S}S\right)\Delta t, \tag{9}$$

which is simplified to the following:

$$\frac{\partial f}{\partial t} + wS\frac{\partial f}{\partial S} + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 f}{\partial S^2} = wf. \tag{10}$$

Equation (10) is the well-known B-S differential equation [28]. This differential equation applies to the pricing of all derivative securities whose price depends on the price of the underlying security S. This equation has different solutions for different derivative securities. Different derivative securities use different boundary conditions when solving this equation. For European call/put options, the basic boundary conditions are as follows:

$$\begin{aligned} f &= \max(S - X, 0), \quad t = T, \\ f &= \max(X - S, 0), \quad t = T. \end{aligned} \tag{11}$$

Combining equation (8) with (11), the pricing formulas of financial market options and import options can be obtained:

$$c = SN(d_1) - Xe^{-w(T-t)}N(d_2). \tag{12}$$

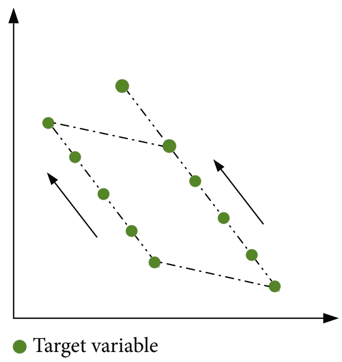

Figure 4: Schematic diagram of the mutation process.

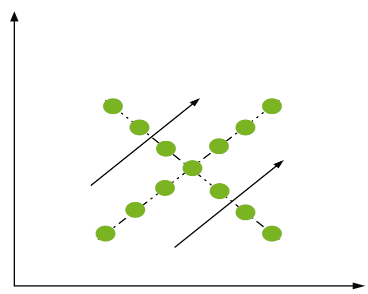

Figure 5: Schematic diagram of the crossover process.

Among them,

$$d_1 = \frac{\ln (S/X) + \left(w + \sigma^2/2\right)(T-t)}{\sigma(T-t)^{1/2}}, \quad d_2 - d_1 - \sigma(T-t)^{1/2}. \tag{13}$$

$N(x)$ is the cumulative function of the standard variable. By invoking the parity formulas $p = c - S + Xe^{-w(T-t)}$ and $N(x) + N(-x) = 1$, the value p of the incremental value t is as follows:

$$p = -SN(-d_1) + Xe^{-w(T-t)}N(-d_2). \tag{14}$$

In formula B-S, the value of an option is based on five variables: the value of the underlying asset, exercise rate, risk-free rate, time to maturity, and underlying volatility. Of these five variables, interest rates and volatility are unknown and the volatility of interest rates and options must be predicted.

When calculating the B-S equation, it is necessary to know whether the derivative security $\mathfrak{J}$ is safe and whether there is a risk. $+(\partial f/\partial S)$ changes as S and t change when it is confirmed that there is no risk. Therefore, the relative proportions of derivative securities and assets should be constantly adjusted to avoid risks.

2.4.2. Basic Particle Swarm Optimization Algorithm. When the p particle is in the D-dimensional position, it forms a population $(x_1, x_2, \cdots, x_p)$ flying at a certain speed. Each particle has the ability to adjust the flight speed and position according to its own flight experience [29]. Among them, the position of each particle can be expressed as $x_i = (x_{i1}, x_{i1}, \cdots, x_{iD})$ and the respective velocity of each particle is expressed as $v_i = (v_{i1}, v_{i1}, \cdots, v_{iD})$, $1 \le i \le p, 1 \le d \le D$. For the ith particle, the best position that the particle has flown is expressed as $q_i = (q_{i1}, q_{i1}, \cdots, q_{iD})$ and the best position that the local particle has experienced $q_g = (q_{g1}, q_{g1}, \cdots, q_{gD})$.

Table 1: Experimental data.

	Industry	Time to market	Option net price
1	Winemaking	20	6.88
2	New energy industry	21	4.79
3	Car industry	25	5.64
4	Electrical industry	22	2.79

$$\begin{aligned} v_{iD}^{k+1} &= v_{iD}^{k} + c_1 \xi \left(q_{iD}^{k} - x_{iD}^{k}\right) + c_2 \eta \left(q_{gD}^{k} - x_{iD}^{k}\right), \\ x_{iD}^{k+1} &= x_{iD}^{k} + v_{iD}^{k+1}. \end{aligned} \tag{15}$$

Among them, c_1 and c_2 are called accelerometers and c_2 is called accelerometers. r_1 and r_1 are usually random numbers between [0,1]. The speed of the particles is controlled in the range of $[-V_{\max}, V_{\max}]$.

2.4.3. Principle of the Differential Evolution Algorithm. $X_{i,G}$ $(i = 1, 2, \cdots, MP) = X_{i,G} = [x_{1,G}, x_{2,i,G}, \cdots, x_{n,i,G}] =$ DEuses the parameter vector of the variable$M$as the population for each generation, and rand(0,1) represents a single ID number created within [0,1] [30].

In the DE algorithm, the creation of the first population is generally obtained from all random obey uniform probability, which is as follows:

$$x_{j,i,0} = \text{rand}\,[0,1]\left(u_j - l_j\right) + l_j, \quad (i = 1, 2, \cdots, MP; j = 1, 2, \cdots, m). \tag{16}$$

The mutation evolution algorithm is to create a new population by changing the individual mutation of the current population. Randomly select 3 different individuals from the current G generation for transformation, mutate, and generate mutant individual $V_{i,G+1}$, namely,

$$V_{i,G+1} = X_{rl,G} + D(X_{r2,G} - X_{r3,G}), \quad r_1 \neq r_2 \neq r_3 \neq i. \tag{17}$$

Among them, r_1, r_2, and r_3 are randomly selected vector serial numbers, which are different from each other and different from the serial number i of a single vector target. F is the differentiation factor. The mutation process is shown in Figure 4.

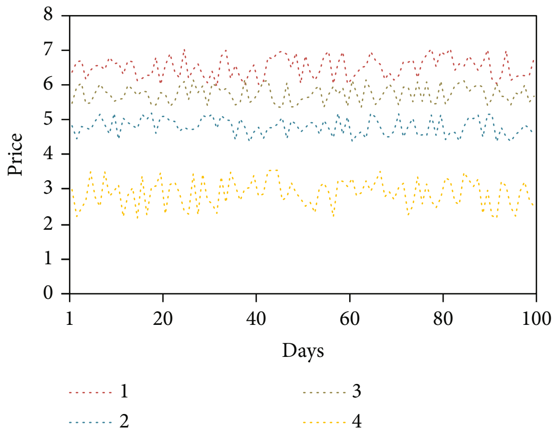

Figure 6: Option pricing volatility.

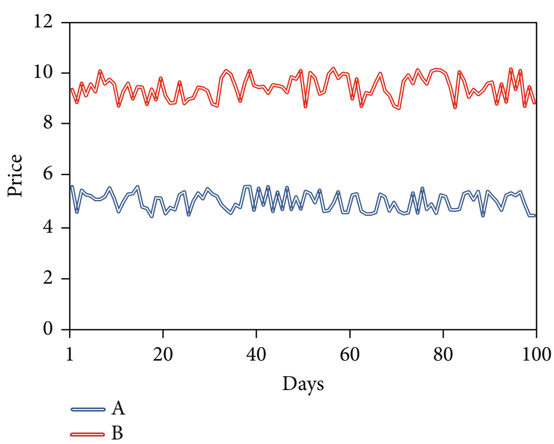

Figure 7: Accuracy comparison chart.

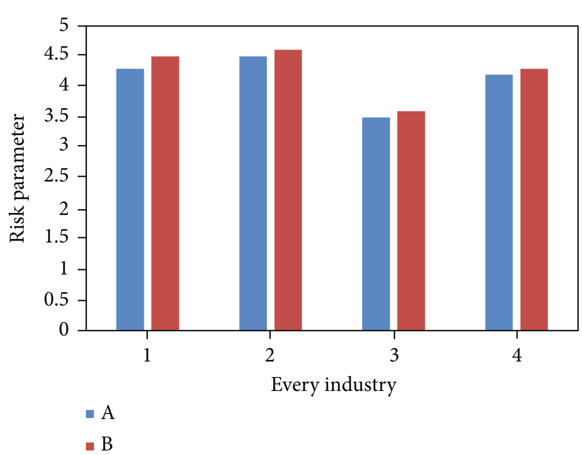

Figure 8: Risk parameter testing.

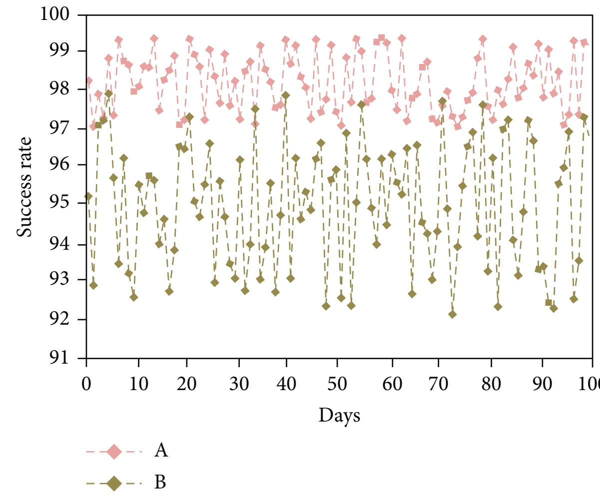

Figure 9: Success rate test.

Using crossover operations to increase the richness of data, the operation process is as follows:

$$U_{i,G+1} = u_{j,i,G+1} = \begin{cases} v_{j,i,G+1}, & \text{if rand } (j) \le CR \text{ or } j = \mathrm{rnd}(i), \\ x_{j,i,G}, & \text{otherwise.} \end{cases} \tag{18}$$

When using the differential evolution algorithm, four running parameters need to be set in advance: (1) The population size is N. For general problems, take 20–50. The larger the N, the stronger the diversity of the population and the greater the probability of obtaining the optimal solution, but the longer the calculation time is. (2) The maximum number of iterations is G. The setting of G depends on the specific problem. The larger the G, the more accurate the optimal solution and the longer the calculation time. (3) The variation factor F is between 0 and 2, usually 0.7. (4) Crossover probability CR, between 0 and 1, usually takes 0.4.

Rand(j) is a uniformly distributed random number between [0, 1], CR is called the crossover probability, and rnd(i) is a random number between $\{1, 2, \cdots, n\}$. The crossover process is shown in Figure 5.

According to equation (18), each test vector $U_{i,G+1}$ is compared with each individual vector $X_{i,G}$ corresponding to the current population and the individual with the best fitting value is selected to enter the next-generation population [31].

3. Option Pricing Model Experimental Design

3.1. Experimental Process. A financial market is selected as the research object, and four options are simulated and simulated, which are tested from the four aspects of error, risk parameters, success rate, and simulation time. After the traditional financial option pricing model is simulated, the computer simulation technology is used to simulate the research again. Then, compare with the actual option pricing results to observe the changes of applying computer

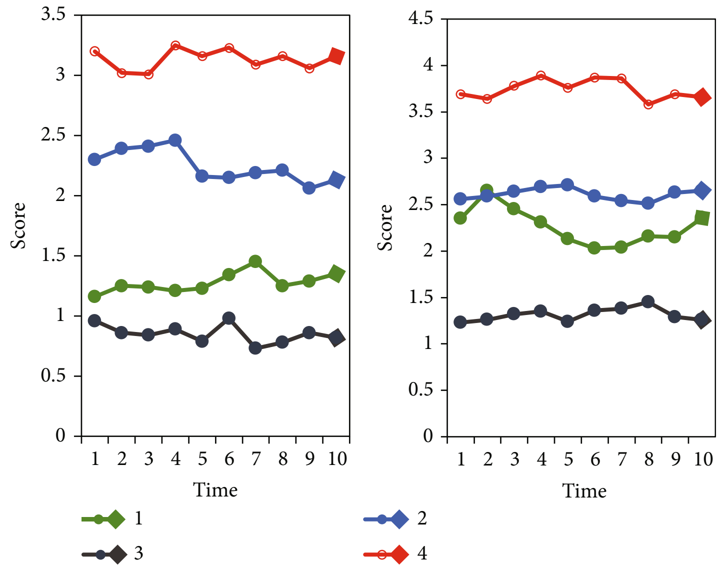

Figure 10: Simulation time test.

simulation technology to the option pricing model compared with the traditional financial option pricing model.

3.2. Experimental Data. Five different industries were randomly selected as the experimental objects, and the specific data of the five experimental objects are shown in Table 1.

3.3. The Purpose of the Experiment. Changes were observed in the application of computer simulation techniques to option pricing models compared to traditional financial option pricing models. Whether it is possible to improve the accuracy and reduce the error is the key to avoid risks.

4. Option Pricing Model Experimental Design Results

4.1. Error Test. In order to ensure the accuracy of the experiment, the simulation experiment of option pricing error is carried out on 4 industries and the 100-day option pricing changes are tested to observe which model has a smaller error between the traditional financial option pricing model and the option pricing model using computer simulation technology. Figure 6 shows the 100-day option pricing fluctuations of four companies, and Figure 7 shows the error comparison chart, where A is the error value of the option pricing model using computer simulation technology and B is the error value of the traditional financial option pricing model.

It can be seen that the option pricing model of the computer simulation technology is closer to the actual financial option pricing, with an average error of less than 6.5%, while the average error of the traditional financial option pricing model is less than 10.3%. It can be seen that the computer simulation technology can more fully analyze the option pricing situation and the simulated data is closer to the actual value. The accuracy rate of the option pricing model using computer simulation technology is higher than that of the traditional financial option pricing model, and the error is smaller.

4.2. Risk Parameter Test. Carry out risk simulation tests on 4 enterprises, among which A is the risk parameter of the option pricing model using computer simulation technology and B is the risk parameter of the traditional financial option pricing model. The results are shown in Figure 8.

It can be that the risk parameter of the computer simulation technology option pricing model is slightly lower than that of the traditional financial option pricing model. The average risk parameter of the computer simulation technology option pricing model of the four companies is 4.125, the risk parameter of the traditional financial option pricing model is 4.25, and the risk parameter is reduced by 3.03%. It can be seen that the application of computer simulation technology to the financial option pricing model can reduce the risk parameters and ensure the stability of the financial market.

4.3. Success Rate Test. The traditional financial option pricing model and the option pricing model using computer simulation technology are tested for the success rate, and the actual pricing of options in 4 industries is tested. The simulation results are compared with the actual results to see which model has a higher success rate. Among them, A is the success rate of the option pricing model using computer simulation technology and B is the success rate of the traditional financial option pricing model. The results are shown in Figure 9.

It can be seen that the success rate of the option pricing model of computer simulation technology is much higher than that of the traditional financial option pricing model. The success rate of the traditional financial option pricing model fluctuates at around 95%, and the success rate of the computer simulation technology option pricing model fluctuates at around 98%. The success rate of the traditional financial option pricing model has a large fluctuation area, and the computer simulation technology option pricing model has a small fluctuation area of the success rate. The success rate of the computer simulation technology option pricing model is more stable than that of the traditional financial option pricing model.

4.4. Simulation Time Test. The simulation time of the option pricing model and the traditional financial option pricing model using computer simulation technology was recorded separately to observe the difference in time between the two, and 10 simulation tests were conducted on 4 industries. The results are shown in Figure 10.

It can be seen that the simulation time of the computer simulation technology option pricing model is lower than that of the traditional financial option pricing model. The average simulation time of the option pricing model of the computer simulation technology is 1.877 seconds, and the average simulation time of the traditional financial option pricing model is 2.482. The computer simulation technology increases the simulation time by 0.605 seconds. It can be seen that the algorithm process of computer simulation technology is simpler and the simulation speed is faster.

5. Discussion

The research on people's understanding of finance begins by challenging the traditional financial market hypothesis and expected utility theory and analyzing and understanding traditional financial science from the perspective of psychology. It not only provides new research methods for financial market research but also brings new research perspectives to financial science research. In this paper, a computer simulation study is carried out from the correlation finance under the stochastic interest rate and an option pricing model is established, which uses the basic particle swarm optimization algorithm and differential evolution algorithm to establish the option pricing model. Although many achievements have been made in the pricing of financial options, due to the influence of external factors, the experimental results will have certain errors, which will not affect the final results, which can greatly reduce the risks existing in the financial market and promote the development of financial enterprises.

6. Conclusion

As an advanced simulation technology, computer simulation technology can bring the simulation results close to the actual results to the greatest extent. In this paper, the B-S option pricing model is used to apply computer simulation technology to the option pricing model and the basic particle swarm optimization algorithm and differential evolution algorithm are used to simulate the relevant financial option pricing under stochastic interest rates. The performance, success rate, risk parameters, and simulation time are superior to traditional option pricing models.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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