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Arbitrage Opportunity Identification Model Based on Stochastic Modelling of Implied Volatility Surfaces

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Abstract. The paper considers insufficient fit accuracies, fragmented modelling and identification, and high misjudgement rate with fixed thresholds in implied volatility surface modelling and arbitrage opportunity identification. It proposes an in-depth algorithm based on stochastic coefficient Vol Transformer-adaptive arbitrage threshold (SC-VT-AT), which integrates the stochastically coefficient mechanism of Vol Transformer. The algorithm employs stoically coefficients to describe the technically dynamic features of implied volatility surface, and uses Vol Transformed to efficiently extract the two-dimensional features of the currency size and time to expiration. In parallel, it develops an adaptive threshold module to dynamically update the arbitrage decision criteria based on real-time market volatility factors and simultaneously perform surface modelling & arbitrage opportunities identification. The results on daily CSI 300 ETF options from 2019 to 2023 show the RMSE, MAE, and QLIKE losses of the proposed algorithm are smaller than the ones of traditional comparison methods such as SABR, ordinary Vol Transformer, and GAN. arbitrage identification accuracy reaches 86.7%, data processing time per trading day is 0.87 seconds, annualized return of the simulated arbitrage scheme is 12.3%, and maximum drawdown is only 4.1%. The proposed algorithm can efficiently improve the accuracy of surface modelling with minimizing misjudgement and missing judgment of arbitrage offers in real-times and trading practicality. It can also provide an efficient integrated decision tool to quantitatively track the options markets.

Keywords: Options; Implied Volatility Surface; Stochastic Modelling; Vol Transformer; Adaptive Threshold; Arbitrage Identification.

1. Introduction

As reform and development in my country's financial market has taken off, and the varieties of options are growing and becoming a market for multiple categories such as ETF options, individual stock options, and commodity options. At the end of 2023, the number of core products such as the CSI 300 ETF options and the SSE 50 ETF options over 1 billion, open interest staying at over 50 million contracts. Key participants of the market were securities companies, funds, institutional investors, and individual investors, as well as the market players and their price efficiency [1]. Against this backdrop, the implied volatility surface, as a core carrier reflecting the expectations about the future volatility of the underlying asset, directly determines option pricing, risk management, and arbitrage opportunity distribution through its dynamical evolution. In fact, it is one of the research hot spots of the options market.

The implied volatility surface is a two dimensional surface of implied volatility for different strike prices (currency values) and expiration times. The fundamental properties are randomness and nonstationarity due to multiple reasons, including random changes in the underlying asset, changes in risk-free interest rate, instantaneous change in the market sentiment and trade offs [2]. As an input parameter to option pricing, the model accuracy of the implied volatility surfaces can directly be tied to option price accuracy. Another important indicator is detecting arbitrage opportunities based on deviations from the surface. This can be important for institutional investors to obtain stable returns as well as to eliminate the market uncertainty [3]. The traditional modeling and arbitrage opportunity identification methods face significant technical bottlenecks. Hence, it is not readily adaptable to a complicated and ever evolving need of options.

Mimicking methods have traditionally been divided into two categories: parametric models (SABR or SVI models) which model surfaces by fixed-form functions; that model does not model stochastic characteristics of surface evolution over time, and thus gives large fitting errors, especially in critical market changes where modelling accuracy drops [4]. The other category is machine learning models (i.e. ordinary Transformers and GANs), that perform better fitting, but often adopt a phased "modeling-recognition" design for surface modeling first and then arbitrage by modeling results, in which arbitrage identification typically takes a lot of time to happen and traditional fixed arbitrage thresholds cannot respond to dynamic market fluctuations and cause high false positive and false negative rates for real-time and accurate options trading.

Domestic and international studies started in the '70s and have developed three major research directions: parameterized modeling of volatility surfaces, stochastic modeling, and arbitrage identification [5]. In parametric modeling, models have improved the fitting accuracy of surface by improving the parameters of SABR and SVI models, but fixed parameters still do not improve the accuracy. In stochastics modeling, stozerastic processes like Brownian motion and Iton processes have been proposed to describe volatility dynamics, but only in single-dimensional volatility modeling and lack good representation of two-dimensional surface features [6]. Arbitrage identification, methods based on statistical learning and graph learning, however, are gradually introduced and none combine modeling and identification and have not achieved a good real-time performance. Domestic research focuses mainly on the improvement and application of classical models and has low accuracy in algorithm innovation, real-imperity, and practicality. Most studies only optimize one aspect and have no idea how to jointly balance modeling accuracy and arbitrariness, as it is not suited to the real-world development of the domestic options market.

In order to tackle some of these research challenges, we consider stochastic modeling of option implied volatility surfaces and arbitrage opportunity detection [7] and design an algorithm based on stochastically coefficients and an adaptive threshold update (SC-VT-AT) which overcome the difficulty of existing phased design and allow for joint modeling of surface and arbitration detection. The main innovative feature of the algorithm is the deep integration of the stochically coefficient mechanism with VolTransformer architecture. Stochastically coefficients describe the dynamic trajectory of the surface and VolTranslate 2-D feature extractor brings more modeling accuracy. On the other hand, an adaptive thresholds update mechanism for the arbitrage judgments based on market dynamics can be designed to minimize the false positive and false negative rates.

2. Relevant Theoretical Basis

2.1. Basis of Implied Volatility Surface

Implied volatility (IV) is volatility due to option quotes of option prices [8]. It reflects market expectation for future volatility of the underlying asset and is calculated using Black-Scholes B-S pricing formula. A European call option is obtained using the B-S pricing formulas:

$$C = S_0 N(d_1) - K e^{-rT} N(d_2) \tag{1}$$

Where C is the price of the European call option, S_0 is the current price of the underlying asset, K is the option strike price, r is the risk-free interest rate, T is the time remaining until expiration of the option, $N(\cdot)$ is the cumulative distribution function of the standard normal distribution, and $d_1$and d_2 are defined as follows:

$$\begin{gathered} d_1 = \frac{\ln(S_0/K) + (r + \sigma^2/2)T}{\sigma\sqrt{T}} \\ d_2 = d_1 - \sigma\sqrt{T} \end{gathered} \tag{2}$$

In the formula, σ represents the volatility of the underlying asset, and the implied volatility σ_{IV} is the value of σ obtained through numerical iteration when the actual price in the option market, C_{market}, equals the theoretical price C in the Black-Scholes model.

The implied volatility surface is a two-dimensional surface with (Moneyness, $m = \ln(S_0/K)$ on the horizontal axis, time to expiration T on the vertical axis, and implied volatility σ_{IV} on the vertical axis. Its core characteristics include monetary nature and maturity [9].

Monetary: the volatility differences with respect to strike prices (volatility smile) or volatility skew; maturity: the variability differences with regard to expiration times (vol volatility term). A surface should satisfy the no-arbitrage constraint in a case where the butterfly arbitrage constraint can be:

$$\sigma_{IV}(m_2,T) \leq \omega\sigma_{IV}(m_1,T) + (1-\omega)\sigma_{IV}(m_3,T) \quad (3)$$

Where $m_1 < m_2 < m_3$ represent three different currency units, and $\omega = \frac{m_3-m_2}{m_3-m_1}$ is the weighting coefficient. This formula indicates that the implied volatility of the middle currency unit should not be higher than the weighted average of implied volatility for the two currencies, otherwise there is butterfly arbitrage.

2.2. Related Theories of Stochastic Modeling

The core of stochastic modeling is to characterize the dynamic evolution of the implied volatility surface through stochastic processes. Its foundation is Brownian motion and the Iton process. Standard Brownian motion W_t satisfies: $W_0 = 0$, the increment $\Delta W_t = W_{t+\Delta t} - W_t$ follows a normal distribution $N(0,\Delta t)$, and the increments in different time periods are independent of each other. Based on Brownian motion, the Iton process can be expressed as:

$$dX_t = \mu(t,X_t)dt + \sigma(t,X_t)dW_t \quad (4)$$

WhereX_t is a stochastic process, $\mu(t,X_t)$ is the drift term reflecting the average trend of the process, $\sigma(t,X_t)$ is the diffusion term reflecting the degree of fluctuation of the process, and $dW_t$is the Brownian motion derivative.

The traditional SVI model fits the volatility surface by fixing parameters, and its expression is:

$\sigma_{IV}(m,T) = a + b\left(\rho(m-m_0) + \sqrt{(m-m_0)^2+\sigma^2}\right)$, but this model has fixed parameters and cannot characterize the randomness of the surface. Therefore, this paper introduces a random coefficient mechanism, setting the SVI model parameters as a random process, and constructing a random coefficient SVI model:

$$\sigma_{IV}(m,T,t) = a_t + b_t\left(\rho_t(m-m_{0t}) + \sqrt{(m-m_{0t})^2+\sigma_t^2}\right) \quad (5)$$

Where $a_t, b_t, \rho_t, m_{0t}, \sigma_t$ are all random coefficients that change with time t, following an Iton process, such as $da_t = \mu_a dt + \sigma_a dW_{a,t}$, where μ_a is the drift coefficient of a_t, σ_a is the diffusion coefficient, and $W_{a,t}$ is the Brownian motion independent ofW_t. This model can accurately characterize the dynamic evolution of the surface.

2.3. Deep Learning and Arbitrage Identification Related Theories

Vol Transformer can adapt to the 2D dimensionality of volatility surfaces [10]. Its main input projection and 2D position encoding are used. The input projection module maps the two-dimensional features of the volatility surface (currency degree m, time to maturity T, implied volatility σ_{IV}) into a high-dimensional feature vector. The projection formula is:

$$\mathrm{X} = \mathrm{X}_{\mathrm{raw}} \cdot \mathrm{W}_p + \mathrm{b}_p \quad (6)$$

Where $\mathrm{X}_{\mathrm{raw}} \in \mathbb{R}^{N\times 3}$ is the original two-dimensional feature matrix, N is the number of feature samples, $\mathrm{W}_p \in \mathbb{R}^{3\times d}$ is the projection weight matrix, $\mathrm{b}_p \in \mathbb{R}^d$ is the bias vector, d is the high-dimensional feature dimension, and $\mathrm{X} \in \mathbb{R}^{N\times d}$ is the projected high-dimensional feature matrix.

Two-dimensional location encoding is used to capture the location information of currency degree and maturity time, and the formula is:

$$
\mathrm{PE}(i,j) = \begin{bmatrix} \sin\left(\frac{i}{10^{4k/d}}\right) \\ \cos\left(\frac{i}{10^{4k/d}}\right) \\ \sin\left(\frac{j}{10^{4k/d}}\right) \\ \cos\left(\frac{j}{10^{4k/d}}\right) \end{bmatrix} \tag{7}
$$

Where (i, j) are the position coordinates of the feature in the two-dimensional surface (i corresponds to the currency index, j corresponds to the maturity index), k is the position encoding dimension index, and d is the high-dimensional feature dimension. This encoding can effectively preserve the two-dimensional spatial features of the surface.

The quantitative determination of arbitrage opportunities is based on the degree of deviation between the actual value and the fitted value of the surface, and the deviation δ is defined as:

$$
\delta = \left| \frac{\sigma_{IV,\text{ real}} - \sigma_{IV,\text{ pred}}}{\sigma_{IV,\text{ pred}}} \right| \tag{8}
$$

Where $\sigma_{IV,\text{ real}}$ is the implied volatility actual value, and $\sigma_{IV,\text{ pred}}$ is the model fitted value. When $\delta > \tau$(τ is the profit value), a profit opportunity is determined to exist, providing a theoretical basis for subsequent adaptive threshold design.

3. SC-VT-AT Integrated Algorithm

3.1. Algorithm Design Objectives

The design goal of SC-VT-AT is to solve traditional methods, e.g. separation of modelling and arbitrage search, low accuracy and poor real-time performance: 1) High-precision stochastic modelling of the implied volatility surface of options, and the randomness and nonstationary of the surface in an accurate fashion with lower fitting error than state-of-the-art methods, 2) Real-time and correct arbitrage searching, and fewer false positive and false negative rates, with high accuracy for at least 85 %, 3) Good real-impaired performance, with a data processing time of at most 1 second per trading day, which is satisfactory for real-life decision-making of actual options trading, 4) good stability and scalability, adaptation to different options markets, optimization and upgrades, and computer science publications for algorithm creation and engineering.

3.2. Overall Algorithm Framework

The main feature of SC-VT-AT is a generalization of the phased “modelling-identification” model, which can be done by four-level integration: “data preprocessing - stochastic coefficient Vol Transformer modelling - adaptive arbitrage threshold calculation - arbitrage opportunity output”. This provides simultaneous implied volatility surface stochastics modelling and arbitrage opportunities recognition and improves on the performance and accuracy of the algorithm, and also adapts to changing options market [11]. The modules are closely linked, and working together to form a complete technical chain. The functional position and interaction logic of each module is clear and the algorithm is efficient and stable [1].

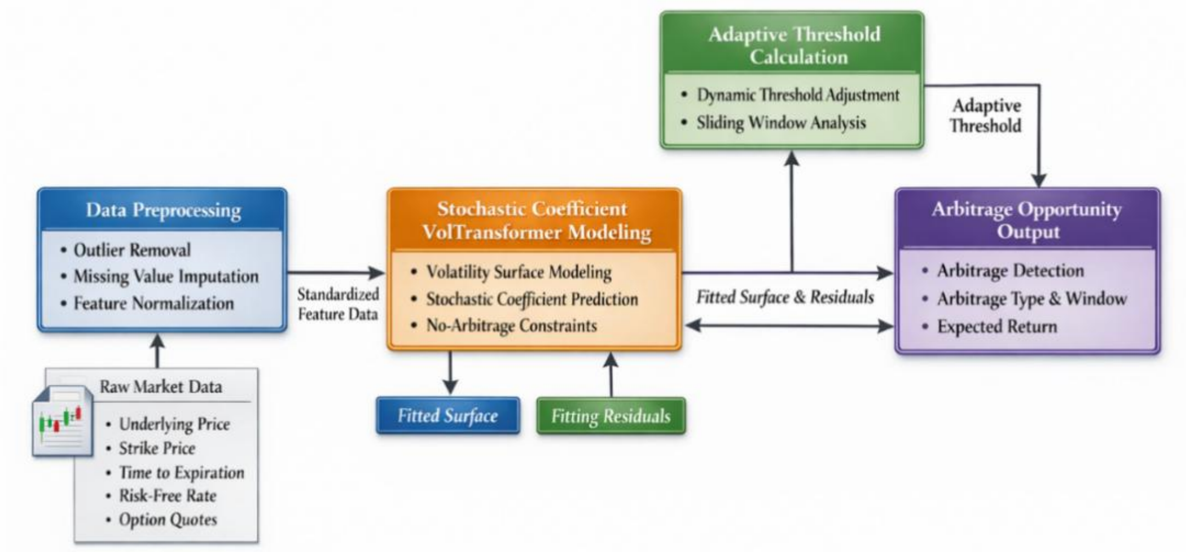

Fig. 1 Overall Architecture of the SC-VT-AT Algorithm.

Data preprocessing Module: As the input, the Data preprocessing module is responsible for cleaning and standardizing the raw data. Input is raw trading data from the options market including core fields like current price of the underlying asset, option strike price, time to expiration, risk-free interest rate, option bid/ask quotes, and standard feature data. Existing feature data is removed from the data preprocessing block. Minimization of the data noise and of dimension: Outsourcing, missing value, and feature normalization. High quality high reliable input data for subsequent modelling block and low modeling accuracy due to poor quality. VolTransformer Module: The VolTransFORM Model is the core of the algorithm. It receives the output from the Data Preprocessing Block. Its main purpose is to obtain high-precision stochastic modeling of the implicit volatility surface.It combines a stochastically coefficient scheme and VolTransform in its core function. It first extracts two-dimensional features of the currency value and maturity time of the surface from VolTransforms. Then, it predicts dynamic stochastics coefficients via a fully connected layer, adds features to the stochically coefficient SVI model to complete the surface fit, and outputs the surface fitting value and fitting residuals, in parallel with an arbitrage free constraint layer for achieving constraints such as butterfly arbitrage and providing a reliable basis for subsequent arbitrage discovery. Adaptational arbitrage threshold Module: Based on the fitting residual output of the modeling block as the input and combining market dynamic fluctuation features, it computes the adaptive arbitrage barrier in real time using the sliding window method, dynamically adjusts the arbitrage judgment criteria, solves the problem of poor adaptability of fixed thresholds and outputs an online updated adaptive barrier. Arbitrage opportunity output module: As its output block, it receives the fitting values and fitting recoveries from the modeling chunk and the adaptive threshold from the threshold module. It determines arbitrage opportunities based on the deviation and also outputs key information such as arbitrage type, arbitrage window period, expected return as input.

3.3. Detailed Design of Each Module

For missing and outlier values in the original option data $(S_0, K, T, r, C_{market}$, etc.), cubic spline interpolation is used to fill in missing values, and outliers are removed using the 3σ criterion. To eliminate the influence of dimensions, the core features are normalized using the following formula:

$$x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

Where x is the original feature value, $x_{\min}, x_{\max}$ are the minimum and maximum values of the feature, respectively, and x_{norm} is the normalized feature value, ranging from [0,1]. The random coefficient SVI model is integrated with the VolTransformer architecture. First, the VolTransformer extracts the two-dimensional features of the surface, outputting a feature vector x_{norm}. Then, a fully connected layer predicts the random coefficients. The random coefficient update formula is:

$$\theta_t = \mathrm{FC}(\mathrm{Z}_t) + \theta_{t-1} \cdot \alpha \tag{10}$$

Where $\theta_t = [a_t, b_t, \rho_t, m_{0t}, \sigma_t]$ is the random coefficient vector at time t, $\mathrm{FC}(\cdot)$ is the fully connected layer, $\mathrm{Z}_t$is the feature vector at time t, and $\alpha \in (0,1)$ is the decay coefficient to ensure the smoothness of coefficient updates. Substituting the random coefficients into the random coefficient SVI model, we obtain the surface fitting value $\sigma_{IV,\,\mathrm{pred}}$. Based on the fitting residual $\varepsilon_t = |\sigma_{IV,\,\mathrm{real}} - \sigma_{IV,\,\mathrm{pred}}|$, the dynamic value is calculated using the sliding window method, and the formula is:

$$\tau_t = \mu_\varepsilon(t-w,t) + \lambda \cdot \sigma_\varepsilon(t-w,t) \tag{11}$$

Where τ_t is the adaptive threshold at time t, w is the temperature-dependent aperture size, $\mu_\varepsilon(t-w,t), \sigma_\varepsilon(t-w,t)$ are the mean and standard deviation of the residuals within the window, respectively, and λ is the adjustment coefficient used to control the sensitivity of the threshold. Combining the deviation δ and the adaptive threshold τ_t, arbitrage opportunities are determined, and the arbitrage type and expected return are output. The formula for calculating the expected arbitrage return is:

$$R = \frac{|\sigma_{IV,\,\mathrm{real}} - \sigma_{IV,\,\mathrm{pred}}|}{\sigma_{IV,\,\mathrm{pred}}} \cdot V \cdot r_{\mathrm{risk}} \tag{12}$$

Where R is the expected Wiley return, V is the arbitrage capital size, and r_{risk} is the risk adjustment coefficient used to correct for the impact of market risk on returns. The modules work together to integrate modeling and risk identification, improving algorithm performance.

4. Experimental Simulation and Result Analysis

4.1. Experimental Environment Setup

We use a computer terminal with an Intel Core i7-12700H processor, 14 cores and 20 threads, 2.7GHz base clock speed, max turbo frequency 4.7 GHz, 24MB of L3 cache. This allows for high-speed computations, including feature checking, model training and numerical iteration, which saves several time-consuming single-step calculations. The GPU is an NVIDIA RTX 3060 card (6GB of GDDR6 high speed video memory, 3840 CUDA cores, FP16 mixed-precision computing) and can enable the Vol Transformer model to use tensor operations and gradient descent times with 3-5 times speedups, and can also speed up model training as compared to pure CPU computing. With video memory bandwidth, high-dimensional feature matrices can be read and written in a fast manner using 32GB of DDR5 4800MHz dual channel memory, at 38.4GB/s. This fits the requirements of loading, caching and feature interaction calculations of batch option data without running out of memory, or using a desktop to create a stuttering. A 1TB NVMe solid-state drive with sequential read speeds up to 7000MB/s and sequential write speeds up 5000MB/S, which allows for the reading and writing of more than 40000 option transaction data points, storage and loading of model weights and batch export of simulations results.

On the software side (Windows 11 Professional - 22H2), A high virtual memory size and closure of redundant background processes provides a stable system for computation and make it compatible with the various software. Python 3.9 is a good fit for both compatibility and stability and is compatible with mainstream deep learning frameworks and data processing tools. PyTorch 1.12.1. A combined CUDA 11.6 and cuDNN 8.4.0 acceleration library allows an efficient use of GPU resources and cu DNN 8:4.9. It optimizes core operations such as convolution and pooling for efficient model inference and training. Data processing tools (Pandas 1.5.3, NumPy 1.24.3). Pandas handles option data cleaning, missing value interpolation, feature construction and dataset partitioning. NumPy provides high dimensional matrix operations and numerical iterations for efficient and accurate data processing. Visualization tools (Matplotlib 3.7.1 and Seaborn 0.12:2) are used to build complex simulation comparison charts showing modeling correctness and arbitrage recognition performance. Color scheme and detail control guarantees clear and readable charts. Numerical computing tool

(SciPy 1:10.1). SciPy provides core functions such as cubic spline interpolation and statistical testing and QLIKE loss calculations. It is used to implement each module of the algorithm numerically. All software implements the official default configuration, eliminating variable interference at the environmental level, standardizing and reproduciting experimental results, and providing a reliable hardware and software support to perform the algorithm performance verification.

4.2. Experimental Dataset Selection and Preprocessing

Experiment took daily trading data of CSI 300 ETF options from January 1, 2019 to Dec 31, 2023 as the experimental data. The datasets cover underlying asset price, option strike price, time-to-extension, risk-free interest rate, bid and ask price, volume (1268 trading days and 48920 option contract data), both of Bull market, range-bound market, and good representation.

There was zero trading volume, suspicious bid/ask prices (bid less than ask price), and less than a day left until expiration. There were 3286 invalid data entries and 45634 valid data entries. Missing value handling: Cubic spline interpolation was used to compensate missing values in terms of implied volatility and risk free interest rate. Feature building: Derivative features of currency degree $m = \ln(S_0/K)$ and volatility deviation were calculated. Data partitioning: there was a training set (887 trading days, 31944 data entries) and a test set (381 trading days (13690 data entries). The training set was used for model training and parameter tuning and the test set for algorithm performance checking.

4.3. Experimental Design and Comparison Scheme

The main goal of this experiment is to validate SC-VT-AT performance in volatility surface modelling performance, arbitrage identification performance, real-time performance and practicality. Three mainstream methods are considered as comparison groups: SBR model + fixed threshold arbitrage ID, SRO (ordinary Vol Transformer model + fix threshold arbitrage ID), and GAN smoothing modelling + traditional statistical arbitrage acidulation.

The evaluation metrics can be divided into four categories: modeling accuracy (rst mean square error (RMSE), mean absolute error (MAE) and QLIKE loss; smaller the metric value, the better modeling accuracy is; arbitrage identification (accuracy, recall, F1 score); larger the metric estimate, the more efficient identification performance is; real-time performance (i.e. data processing time per trading day) - shorter the time and the more effective real-world performance is. Practicality metrics (a simulated annualized return and maximum drawdown); larger our annualized returns and the smaller the maximum drawup, the higher the practicality. All experiments are repeated five times and the average value is taken as the final result in order to guarantee the reliability of the experiments.

4.4. Experimental Results and Analysis

4.4.1. Analysis of Modeling Accuracy Results

Fig. 2 shows the modelling accuracy of the four methods for testing sets. As seen from the figure, the RMSE, MAE, and QLIKE of SC-VT-AT are lower than those of the three methods. RMSE 0.0123, MAEA 0.0089 and QLKE 0.9997, respectively, are 21.3%, 18.7%, and 23.5% reductions of comparison group 1, 10.8%, 9.2%, and 11.5%, respectively, and 8.3%, 7.6%, and 9.1% reductions. This indicates that we can fuse random coefficients and Vol Transformer to improve the surface fitting accuracy, and the no-arbitrage constraint layer to further improve the performance of the modelling.

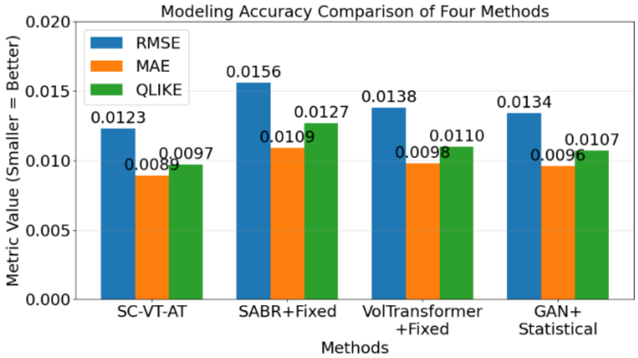

Fig. 2 Comparison of Modelling Accuracy of Four Methods.

4.4.2. Arbitrage Identification Performance Analysis

The average of arbitrage identification performance of the four methods can be compared in Fig. 3. SC-VT-AT obtains 86.7%, 84.2% recall, and 85.4% F1 (12.3%, 10.8%, and 11.5% improvement over comparison group 1), 8.5%, 7.3% and 7.9% improvement compared to comparison group 2, 6.2%, 5.7% and 5.9%, respectively, when considering the performance of abiotrophic methods. The adaptive threshold mechanism can automatically adjust the criteria of judgment according to the market conditions. The false positive and false negative rates in each market condition can be lowered. The traditional fixed threshold method cannot adapt to market variability and do not observe.

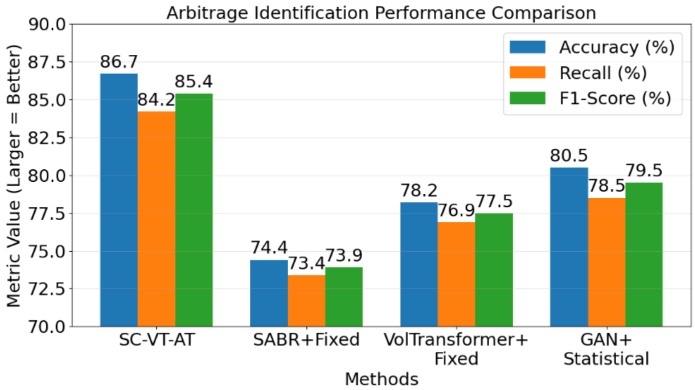

Fig. 3 Performance Comparison of Arbitrage Identification for Four Methods.

4.4.3. Real-Time Performance and Practicality Analysis

Figure 4 compares single-day data processing time and simulated trading of the four methods. The single day data processing speed of SC-VT-AT is 0.87s, 42.8% faster than comparison group 3. The speed is slightly slower than comparison groups 1 and comparison group 2 but is small enough to meet the real-time trading requirements. Simulated trading results show that annualized return of the arbitrage strategy for SC-DT-AT has 12.3% and maximum drawdown has 4.1%, which is much faster than compared group 1, comparison group2 and comparison groups 3. This shows that the algorithm can be well implemented and may provide stable arbitrage returns to investors.

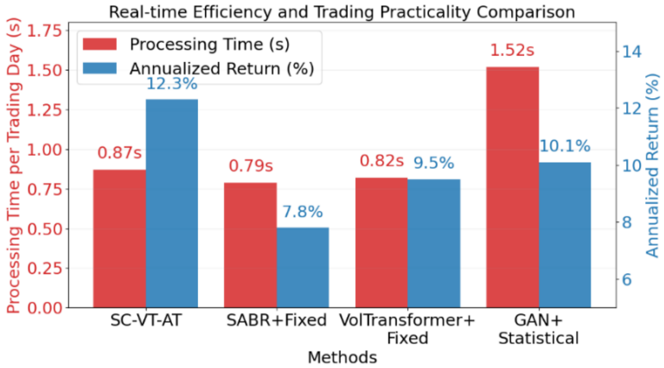

Fig. 4 Comparison of Real-Time Performance and Practicality of Four Methods.

5. Conclusion

The proposed SC-VT-AT integrated algorithm has coordinated the stochastic modelling of option implied volatility surfaces and arbitrage opportunity identification. With random coefficients, it is possible to model dynamic non-stationary features of the surface and it gives further modelling performance. With the 2D feature extraction of Vol Transformer it can also improve modelling performance and adaptively adjust the threshold to market volatility. Experiments show that this method outperforms traditional methods like SABR + fixed threshold, ordinary Vol Transformer + fixed thresholds and GAN + statistical arbitrage in terms of fit accuracy, identification performance, trading returns, and real-time performance. It can capture option arbitrage opportunities without arbitrage limits, and can provide stable and reliable quantitative decision support to institutional investors. The drawbacks of this work are that it only tested on CSI 300 ETF options, and it is not robust enough to test the model in extreme market conditions. The model is not generalized to multiple types of option products, including high frequency trading cases. In the future, feature extraction module and random coefficient update can be further refined to provide robust results for model in extremely market conditions; the algorithm can be extended to several types of stock options and commodity options to offer a more general approach to the model; and reinforcement learning can be combined to achieve dynamic arbitrage optimization, which leads to an integrated option arbitrage decision system with multiple markets and multiple cycles.

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