Energy Economics 122 (2023) 106683

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

High return and low risk: Shaping composite financial investment decision in the new energy stock market

Qing Zhu [a,b], Xiaobo Zhou [a], Shan Liu [b,c,*]

[a] International Business School, Shaanxi Normal University, Xi'an 710061, China
[b] School of Management, Xi'an Jiaotong University, Xi'an 710049, China
[c] Logistics Science and Technology Innovation Integrated Development Center, Xi'an Jiaotong University, Xi'an 710049, China

ARTICLE INFO

Keywords:
Green finance
Portfolio selection
Trend forecasting
Algorithmic trading
Return

ABSTRACT

As an emerging market, the new energy stock market is characterized by high volatility and instability, and investors seeking to make investment decisions face significant challenges. To enable investors to diversify risk and obtain more consistent high returns, we have built a composite financial investment decision system that combines portfolio selection, trend forecasting, and quantitative trading. The system takes a sequential, rolling Sharpe ratio calculation and dynamically selects portfolios to reduce risk from market changes and achieve optimal portfolio diversification. Then, the variational mode decomposition (VMD)-bidirectional gated recurrent unit (BiGRU) model is introduced to predict the trend of the portfolio and quantify the trades of the portfolios. Experimental results show that the system can obtain an average annual return of up to 758,508 CNY with a principal capital of 30,000 CNY. Compared with observing the investment ratio of the portfolio statically, selecting the portfolio by calculating the Sharpe ratio continuously and rolling can improve the portfolio return and diversify the risk. In terms of trend forecasting, VMD-BiGRU is shown to greatly improve forecasting performance compared to single gated recurrent unit (GRU) or long short-term memory (LSTM) models. Compared with human-driven trading, quantitative trading has been shown to have the advantage of short holding times, low risk, and high returns by capturing trading opportunities promptly based on the results obtained from predictive models.

1. Introduction

China's energy consumption structure has long been dominated by coal, which has placed a huge burden on China in environmental terms (Sun et al., 2019; Bai et al., 2019; Zhu et al., 2021). The development of new energy is of great significance to China's dependence on traditional energy sources, the protection of the natural environment, and transforming the mode of economic development (Lin and Chen, 2019). In recent years, the new energy industry has developed rapidly, and it is now among the strategic emerging industries in China (Lin and Chen, 2019). The rapid development of new energy has also attracted the attention of investors in the capital market and has provided new investment opportunities (Elsayed et al., 2020; Wang et al., 2022b). Recently, the number of new energy listed companies and the amount of investment have continued to increase; according to Bloomberg, global investment in new energy companies has reached $92 trillion in 2021 and $173 trillion over the next few years (Bloomberg, 2021). Therefore, it is crucial to study and analyze the new energy stock investment market, which can help new energy companies to finance and promote their development and help investors make investment decisions and reduce investment risks.

For investors, new energy stock investment mainly includes portfolio selection, portfolio trend forecasting, and quantitative trading, which are not simple tasks. As an emerging market, the new energy stock market is highly unstable, and investors face significant challenges when making investment decisions (Bai et al., 2019; Wang et al., 2021). Lin and Chen (2019), Dutta (2017) and Wen et al. (2014) pointed out that there are two-way spillover effects and volatility continuity between fossil energy markets, such as coal, oil, and natural gas, and new energy markets, indicating that the volatility of fossil energy markets may be transmitted to the new energy stock market (Sadorsky, 2012). Also, the instability of the international political environment, the volatility of financial markets, and the occurrence of extreme events increase the risk of the new energy stock market (Chen et al., 2020), making it more difficult for investors to make investment decisions.

To help investors make better investment decisions, three questions need to be considered: (1) how to choose a portfolio that is robust and

* Correspondence to: No. 28 Xianning West Road, Xi'an 710049, China.
E-mail addresses: zhuqing@snnu.edu.cn (Q. Zhu), zhou_xiaobo@snnu.edu.cn (X. Zhou), shanliu@xjtu.edu.cn (S. Liu).

https://doi.org/10.1016/j.eneco.2023.106683
Received 19 September 2022; Received in revised form 24 February 2023; Accepted 13 April 2023
Available online 24 April 2023
0140-9883/

reliable with high returns in the new energy stock market, (2) how to deal with data characteristics and predict the future trend of portfolios (up or down), and (3) which trading strategy should be chosen and what the returns will be. Although considerable literature on new energy market investments addresses these issues, research tends to study only some of these problems. Therefore, the objective of this paper is to build an integrated financial system that integrates portfolio selection, portfolio prediction, and quantitative trading to help investors improve the efficiency and profitability of their investment decisions in the face of the complex and volatile new energy stock market.

In this paper, we propose a composite financial quantitative trading system that consists of three main parts: a portfolio selection module, a feature processing and prediction module, and an automatic quantitative trading module. In the stock selection module, we calculate the Sharpe ratios of new energy stocks on a continuous rolling basis: the three with the highest Sharpe ratios form the experimental group, while the three with the lowest Sharpe ratios form the control group. In the feature processing and prediction module, to improve the prediction accuracy of the model, we use variational mode decomposition (VMD) to preprocess the raw time series of the experimental and control group investment portfolios and then input the processed data features into the bidirectional gated recurrent unit (BiGRU) neural network to predict the up and down trends of the portfolios. In the quantitative trading module, we automatically quantitatively trade the stocks of the experimental and control groups based on the prediction results of the VMD-BiGRU model and then calculate and compare their final return values.

The experimental results in this paper show that, with an investment capital of 30,000 CNY over 15 months, the experimental group selected by this complex financial investment system achieved a return amount of 948,135 CNY through prediction and automatic quantitative trading in the new energy stock market through deep learning, and the control group achieved a return amount of 232,524 CNY. The return amount of the experimental group was four times that of the control group in the same principal amount, proving the ability of the Sharpe ratio to reflect the investment value and risk of the portfolio in the financial market. Also, facing the complex, highly uncertain, and volatile new energy stock market, the VMD-BiGRU forecasting model used in this paper demonstrates higher forecasting accuracy than single models, such as gated recurrent unit (GRU) and long short-term memory (LSTM).

The main contribution of this paper is as follows: (1) A complex, versatile, and efficient integrated financial quantitative trading system with strong practical application is designed to provide investors with advice on investment decisions. (2) The hybridization of the dynamic use of Sharpe ratios for portfolio selection with a deep learning-based forecasting and decision-making process in this system significantly enhances the profitability of the quantitative trading system. (3) This is a typical process of characterization from economics theory to data-driven applications and, finally, to computational science practice with complex cross-theoretical innovations.

The structure of this paper is as follows. Section 2 explores the relevant literature in the field of new energy financial markets and quantitative investments. Section 3 shows the design ideas and steps of the quantitative financial investment system proposed in this paper. Section 4 presents the specific details of the data and model parameters used in the model. Section 5 and Section 6 give the experimental results of the model and further analysis, and Section 7 summarizes the conclusions.

2. Related work

In general, stock investment decision making is a complex task. Various factors such as asset allocation, stock selection, risk management, price forecasting, timing trading, statistical arbitrage, and other factors need to be considered in the process of making stock investment decisions. In this section, we review the relevant literature from the three aspects of portfolio selection, trend prediction, and quantitative trading and discuss the similarities and differences between this paper and previous studies.

Portfolio selection. Due to the risks associated with volatility and uncertainty in the new energy stock market, investors need to choose the best investment strategy to minimize risk and maximize returns (Koratamaddi et al., 2021). Markowitz (1952) developed portfolio selection theory, which changed the way investors invest, and made pioneering contributions to the field of financial economics. Based on variance and correlation, Markowitz's modern portfolio theory (MPT) model suggests that rational investors choose an efficient portfolio that provides the highest return for a given risk or the lowest risk for a given return (Mitra et al., 2003). As one of the most commonly used indicators to measure the return and risk of a portfolio, the Sharpe ratio measures the return per unit risk, based on which the mean–variance (MV) model aims to find the portfolio with the highest Sharpe ratio (Sharpe, 1998). Based on the MV model, Chen et al. (2020) used the robust portfolio (RP) model to improve the performance of the new energy stock market portfolio and found that the method performed better in the new energy stock portfolio. The MV model and linear programming (LP) model were used by Kim and Kim (2018) to determine the optimal ratio between long-term and spot contracts; the researchers concluded that this ratio was 89.72% and 10.28%, respectively. Gargallo et al. (2022) dynamically selected the optimal minimum variance portfolio by calculating the asset return variance and covariance for each period using asymmetric dynamic conditional correlation models (ADCC)-generalized auto regressive conditional heteroskedasticity (GARCH), showing that investment in new energy sources has been preferable to traditional fossil energy sources during COVID-19. The above literature shows that return, variance of returns, and Sharpe ratio metrics are widely used in assessing portfolio returns and risks; however, studies in the literature, such as (Kim and Kim, 2018) and Bai et al. (2019) tended to examine the Sharpe ratio of a portfolio statically over time without considering its nonstationarity and nonrobustness. In addition, Chen et al. (2020) and Gargallo et al. (2022) focused on the performance of MV models on portfolios and contributed to the construction of more stable and efficient portfolios, but their studies lacked further trading practice and return measurement in real stock markets.

Portfolio trend forecasting. Because the stock price series is noisy, chaotic, nonsmooth, and nonlinear, it is very challenging to forecast and analyze (Shah et al., 2019). As an emerging market, and one influenced by several related energy financial markets, the new energy stock market has higher volatility and risk (Bai et al., 2019). The mainstream methods in the field of stock market analysis fall into two main categories: (1) technical analysis, which mainly uses historical data such as capital flows, momentum, trend, volatility, and so on to calculate relevant indicators to predict the future ups and downs of the stock price, and (2) fundamental analysis, which mainly looks for economic factors influencing stock price trends, such as macroeconomic, industry, and company analysis (Henrique et al., 2019).

Statistical methods, such as the auto regressive integrated moving average model (ARIMA) and regression, are often used to predict and analyze stock price trends. Predictive regression models were used by Narayan (2019) to study the predictive power of oil price news on stock returns, and Iyke et al. (2021) used predictive regression to forecast energy stock returns by constructing energy security-related indicators. Wang et al. (2022c) compared the performance of classical time series models such as the auto regression moving average (ARMA) and GARCH models in predicting the stock prices of new energy vehicle companies and developed a hybrid model based on a combination of time series and cloud models to further improve prediction accuracy.

Statistical models usually assume that time series data are linear and smooth; however, the time series data of the new energy stock market do not meet this description. Hence, statistical models can play a limited role in forecasting the new energy stock market (Shah et al., 2019). Chong et al. (2017) believed that machine learning and deep learning can extract useful and deep features from the chaotic, nonlinear, and nonstable time series of the stock financial market to achieve more accurate forecasts. Ben Jabeur et al. (2021) compared the performance of seven advanced machine learning types, including random forest, neural network, LightGBM, and CatBoost, on oil price prediction using metrics such as green energy and environmental factors. Gu et al. (2022) constructed a Markov-LSTM model to predict stock prices in the new energy sector and demonstrated that the system is better suited for markets with high volatility and strong stochasticity.

Quantitative trading. According to the different trading agents, trading strategies in the new energy stock market can be mainly divided into human-driven and machine-driven. In the traditional stock market domain, most stock buying and selling transactions are decided and completed by investors. Traditional economists tend to derive simple and perfect economic models under the assumption that investors are perfectly rational, markets are frictionless, and market information is complete; thus, they discuss the optimal investment decisions of investors under this assumption. However, this is not the case in real financial markets (Daniel and Hirshleifer, 2015; Arthur, 2021). Numerous behavioral economics studies point out that investors' growth experience, personality factors, emotional changes, and even the weather may affect their financial investment decisions, causing them to deviate from optimal strategies (Oehler et al., 2018; Rao and Zhou, 2019). Moreover, cognitive biases, such as overconfidence, representativeness bias, framing effect, anchoring effect, and loss aversion, are the underlying reasons for investors' deviation from optimal decisions (Gal and Rucker, 2018; Cho et al., 2017; Nabi et al., 2020). Under the effect of psychological deviation, investors deviate from the optimal decision, which reduces or even transforms the high return they could have obtained into a loss. The financial investments made by investors are often characterized by long holding times and low trading frequency, which makes them vulnerable to overnight and holiday fluctuations and generates large profits and losses, increasing the risk borne by investors (Wu et al., 2019).

Machine learning models can avoid this shortcoming and predict stock trends by calculating and analyzing large amounts of historical data when making buying and selling decisions (Heaton et al., 2017). Compared with investor decisions, machine-driven quantitative trading can circumvent investor psychological biases and combine macroeconomic variables, market structure variables, stock valuation factors, stock growth factors, market sentiment, and many other relevant variables for quantitative analysis to capture investment opportunities and expand investment space (Cheng et al., 2019). The development of financial software and web pages has further increased the number of sources of equity-related information, facilitating the role of quantitative trading. In addition to circumventing investor psychological bias, quantitative trading can achieve returns that cannot be achieved by ordinary investments (Ta et al., 2020). In statistical arbitrage and cross-period arbitrage, quantitative trading can track portfolio trends in real time and capture arbitrage opportunities in a more timely and accurate manner, allowing for rapid trading and gains (Zhuang et al., 2022).

A review of the relevant literature from three perspectives – portfolio selection, trend forecasting, and trading strategy – reveals the complexity of financial decisions faced by investors in the stock market and the efforts made by many scholars for them. A comparison of the relevant literature is presented in Table 1. Most scholars tend to provide advice on some parts of investors' investment decisions from a single perspective, while there are still fewer studies related to an integrated decision-making system, from portfolio selection to trend forecasting to quantitative trading. Therefore, this paper aims to provide investors with a comprehensive and composite multifunctional financial investment decision system. The detailed design of the model is shown in Section 3.

3. Materials and methods

3.1. The proposed model architecture

To enable investors to obtain higher returns, this paper proposes a composite system of financial decision making and quantitative trading based on VMD and BiGRU and applies it to the new energy sector of China's securities market. Suppose that the new energy sector stock pool X consists of n stocks, denoted as $(x_1, x_2, \ldots, x_n)$, the core purpose of this decision system is to select the optimal stock portfolio, forecast it accurately, and capture the buying and selling opportunities in time for automatic quantitative trading. Considering the complexity of the composite financial investment decision system design, this paper follows the principle of simplifying the complex investment decision task into a portfolio selection module, trend forecasting module, and algorithmic trading module according to the function and purpose. The first module was used to select portfolios, while the remaining two modules were used to predict and backtest the returns of the portfolios selected in the first. Compared with the complex all-in-one model, the modules of the split investment decision system remain independent and closely related to each other, which facilitates the understanding of the portfolio performance strengths and weaknesses in each aspect and helps to independently observe the contribution of the three submodules to the final revenue results, while echoing the three issues mentioned in the Section 1. The specific details of the model are shown in Fig. 1, and the steps are as follows.

Step 1: Portfolio selection

Sort all the stocks $(x_1, x_2, \ldots, x_n)$ in the new energy stock pool X according to the Sharpe ratio; then, select the top three stocks to form the experimental group G_E and the bottom three to form the control group G_C.

Step 2: Technical index calculation

In addition to raw data, such as opening price, closing price, highest price, and lowest price, various stock technical indicators, such as rate of return, volatility, and momentum indicators of stock x_i in G_E and G_C, are further calculated.

Step 3: Feature decomposition

Decompose raw data and technical indicator series of stock x_i in G_E and G_C into different modes with VMD.

Step 4: Data labeling

Label the target variable as (0,0,1), (0,1,0), or (1,0,0) based on the closing price of stock x_i in G_E and G_C.

Step 5: Label prediction

The subseries obtained after VMD decomposition and label data are fed into a BiGRU model as input variables for a seven-day period from timestamp $t-6$ to t to predict the label for timestamp $t+1$.

Step 6: Algorithmic trading

Based on the prediction results of the BiGRU model and the closing price, the algorithm conducts high frequency buying, selling, and holding transactions for stocks and calculates the final return of the portfolio and stock.

3.2. Portfolio selecting: Sharpe ratio

The Sharpe ratio is the average excess return an investor earns per unit of risk (Sharpe, 1964). The formula is as follows:

$$S_p = \frac{R_p - R_f}{\sigma_p} \tag{1}$$

where R_p is the return of the portfolio, R_f is the risk-free return, and σ_p is the standard deviation of the excess return of the portfolio. To measure the stock return under the unit risk, we calculated the Sharpe ratio of each stock in the new energy stock pool and sorted all stocks according to the Sharpe ratio. We take a continuous rolling method to calculate the Sharpe ratio and update the portfolio. The specific process is shown in Fig. 2, where SH_i is denoted as the set of Sharpe ratios in stage i.

Table 1
Comparison of the financial investment literature.

Reference	Method	Features	Paper purpose	Portfolio selection	Trend forecast	Trading strategies
Antonakakis et al. (2018)	Spillover index approach, Dynamic correlation coefficient model	Absolute return, volatility	Study the volatility spillover and co-movements between oil and gas company stock prices and explore the optimal weight and hedge ratio in the portfolio	✓	×	×
Kim and Kim (2018)	MV portfolio, LP model, Fuzzy AHP	Tangible factor, intangible factor, the expected cost, cost standard deviation	Improve the stability of LNG imports	✓	×	×
Bai et al. (2019)	Conventional robust portfolio	Covariance and expected return	Improve the performance of new energy equity portfolios	✓	×	×
Gargallo et al. (2022)	ADCC-GARCH	Financial return, closing price	Analyze the impact of clean energy on investor risk level	✓	×	×
Narayan (2019)	Time series cloud model	Data of the automotive industry, stock indicator information	Forecast the stock price of new energy vehicle enterprises	×	✓	×
Ben Jabeur et al. (2021)	LightGBM, CatBoost, XGBoost, RF, neural network models	Closing daily price	Forecast oil prices during COVID-19	×	✓	×
Gu et al. (2022)	Markov-LSTM	Closing daily price	Explore stock price fluctuations in the new energy market	×	✓	×
Wang et al. (2022c)	Predictive regression models	Oil price news, stock market risk factors, stock market price returns	Explore the impact of oil price news on stock returns	×	✓	×
Iyke et al. (2021)	Fama–French three factor model	10 energy security indexes	Explore the predictive power of energy security on the returns of energy stocks	×	✓	×
Li et al. (2014)	Media-Aware quantitative trader	Financial news, financial discussion board, stock transaction	Propose media-aware trading strategies to study the impact of media messages on stocks	×	✓	✓
Wu et al. (2019)	LSTM	Raw financial data	Explore efficient quantitative trading systems	×	✓	✓
Liu et al. (2020)	Adaptive trading model	Historical prices and volumes	Find a balance between exploration and exploitation of the trading agent	×	✓	✓
Wang and Luo (2021)	Empirical mode decomposition (EMD), Interval type-2 intuitionistic fuzzy neural network with GRU	Financial data	Build an intelligent quantitative trading system	×	✓	✓
This paper	MPT, BiGRU	Financial indicators, raw financial data, technical indicators	Construct a composite financial investment decision system	✓	✓	✓

3.3. Technical indicators

The input indicators used in this paper fall into two main categories: raw time series and technical indicators. The raw data mainly include the opening price, highest price, lowest price, closing price, and trading volume; technical indicators include the logarithmic rate of return, volatility, momentum indicators, relative strength indicators, and so on. Details of all the indicators used in this paper are shown in Table 2.

3.4. Feature decomposition: VMD

The representation of data features plays an important role in the performance of the model; thus, reconstructing the original data features and inputting them into the prediction model can effectively improve its performance (Zhu et al., 2022). As one of the latest and more popular information-processing techniques, VMD is widely used in nonstationary time series-related problems (Dragomiretskiy and Zosso, 2014; Li and Wei, 2018; Lahmiri, 2016). In this paper, VMD was used to decompose the original stock price series f into k number of band-limited discrete subseries u_k. The iterative variational framework obtains u_k and ω_k by minimizing the bandwidth of each component to find the optimal solution of the problem. The procedure for a constrained variational problem is as follows:

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[(\delta(t) + \frac{j}{\pi t}) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \quad s.t. \sum_k u_k = f \tag{2}$$

where f represents the original input financial time series, $\{u_k\} = \{u_1, \cdots, u_k\}$ and $\{\omega_k\} = \{\omega_1, \cdots, \omega_k\}$ represent the financial time series subsequence and its corresponding center frequency, K is the number of decomposed sequences, u_k is the kth financial time series subsequence, $\delta(t)$ represents the Dirac distribution, and $*$ is the convolution operator.

3.5. Target variable labeling

Sezer and Ozbayoglu (2018) proposed setting a sliding window and marking the daily closing price according to its highest and lowest points. Based on this, this study designed a three-day sliding window. The closing price on day t is marked (1, 0, 0) ("sell") when the closing price on that day is the highest value of the closing prices of the three days $(t-1), t, (t+1)$. When it is the lowest closing price of the three days, it is marked (0,0,1) ("buy"), and when neither of the above conditions is met, it is marked (0,1,0) ("hold").

Table 2
Technical indicators.

Name	Description	Formulation	Parameter
OP_t	Open price	–	–
CL_t	Close price	–	–
HI_t	High price	–	–
LO_t	Low price	–	–
VO_t	Trading volume	–	–
R_t	Logarithmic rate of return	$R_t = \ln\left(\frac{CL_t}{CL_{(t-1)}}\right)$	–
$VOL(x)_t$	Volatility	$VOL(x)_t = \sqrt{\frac{\sum_{t=1}^{x}\left(R_t-\bar{R}\right)^2}{x-1}}$	$x = 5$
R_{1t}	–	$\ln\left(\frac{HI_t}{OP_t}\right)$	–
R_{2t}	–	$\ln\left(\frac{HI_t}{OP_{(t-1)}}\right)$	–
R_{3t}	–	$\ln\left(\frac{HI_t}{OP_{(t-2)}}\right)$	–
R_{4t}	–	$\ln\left(\frac{HI_t}{OP_{(t-3)}}\right)$	–
R_{5t}	–	$\ln\left(\frac{HI_t}{LO_{(t-4)}}\right)$	–
$MTM(x)_t$	Change in stock price over last x-days	$MTM(x)_t = CL_t - CL_{(t-x)}$	$x = 5$
$RSI(x)_t$	Relative strength index	$RSI(x)_t = 100 - \frac{100}{1+\frac{averagegain}{averageloss}}$	$x = 5$
$ATR(x)_t$	Average true range	$ATR(x)_t = \frac{1}{x}\left(ATR_{(t-1)} \times (x-1) + TR_t\right)$, $TR_t = \max\left\{\begin{array}{l}\left(HI_t - LO_t\right), \\ abs\left(HI_t - CL_{(t-1)}\right), \\ abs\left(LO_t - CL_{(t-1)}\right)\end{array}\right\}$	$x = 5$
$MA(x)_t$	X-days moving average	$MA(x)_t = \frac{1}{x}\sum_{i=1}^{x} CL_{(t-i)}$	$x = 5$
$LL(x)_t$	X-days lowest price	$LL(x)_t = \min\left\{LO_{(t-x)}\right\}$	$x = 5$
$HH(x)_t$	X-days highest price	$HH(x)_t = \max\left\{HI_{(t-x)}\right\}$	$x = 5$
$ROC(x)$	Price rate of change	$ROC(x) = \frac{CL_t}{CL_{(t-x)}} \times 100$	$x = 5$
$BIAS$	X-days bias	$BIAS = \frac{CL_t - MA(x)}{x}$	$x = 5$

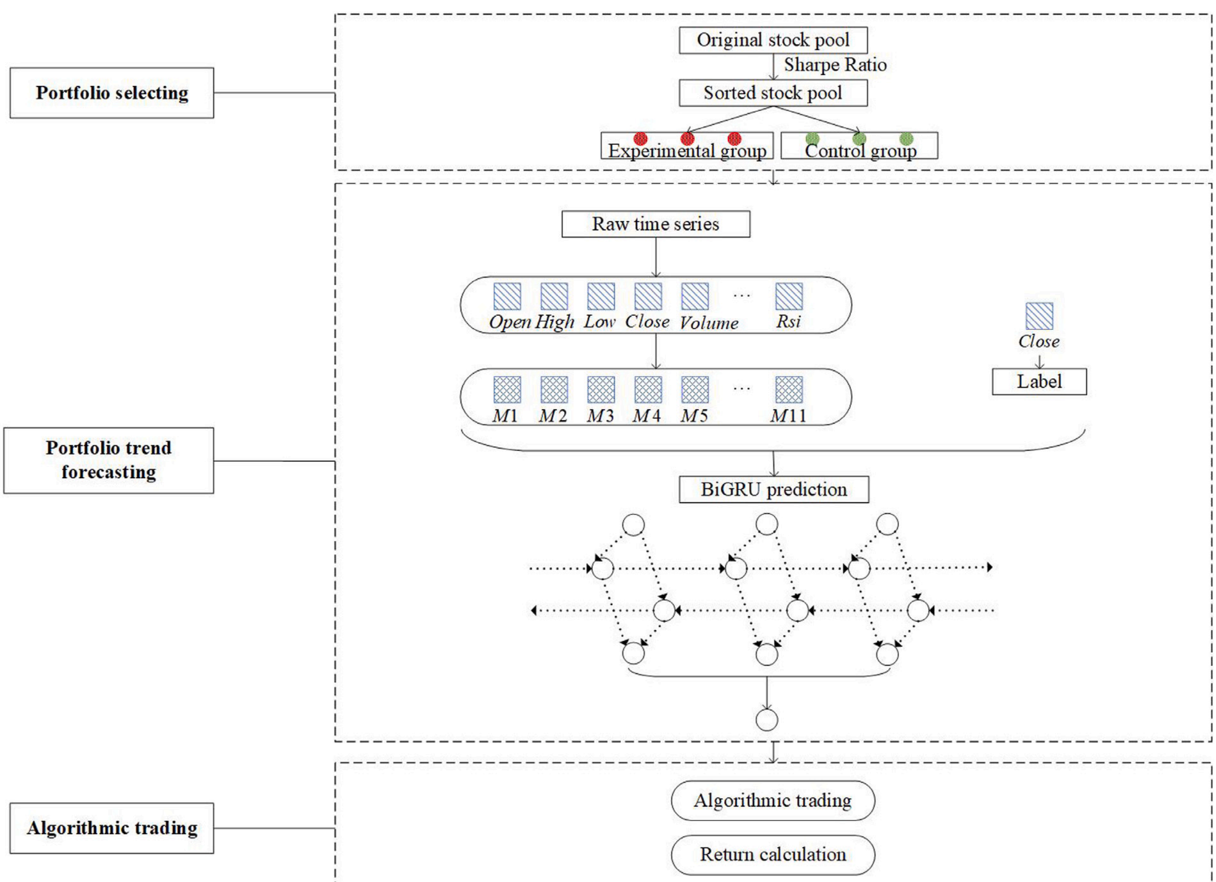

Fig. 1. Architecture of the proposed model.

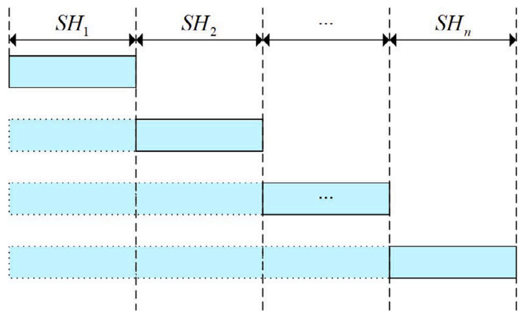

Fig. 2. Sharpe ratio calculation procedure.

3.6. Portfolio forecasting: BiGRU

Recurrent neural networks (RNN) are a variant of artificial neural networks, and the introduction of recurrent units allows RNN to memorize historical inputs and thus perform better in predicting continuous sequence data (Fan et al., 2017). The LSTM model proposed by Hochreiter and Schmidhuber (1997) solved the gradient disappearance problem of the RNN model, enabling it to learn dependencies over a long time span. Based on the LSTM model, the GRU model simplifies the internal structure and operation process. A GRU unit consists of an update gate and a reset gate, which are responsible for controlling how much previous information is retained and what historical information is ignored, respectively (Li et al., 2022). This study used a bidirectional GRU model to predict future trends in financial markets. Because the current price of the financial market is the reflection of the historical price and the basis for the formation of the future price, this study believes that there is a two-way relationship in the financial time series. The bidirectional RNN model proposed by Schuster and Paliwal (1997) can process both past and future financial time series data with forward and reverse information simultaneously, thereby improving the prediction accuracy of the model. The simple structure of the GRU is shown in Fig. 3, and the mathematical expression of the GRU is as follows:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{3}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{4}$$

$$\tilde{h}_t = \tanh(W \cdot [r_t * h_{t-1}, x_t]) \tag{5}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h} \tag{6}$$

$$y_t = \sigma(W_o \cdot h_t) \tag{7}$$

z_t and r_t denote the update gate and reset gate, respectively. x_t indicates the input, and h_t represents the hidden state at time t. $\tilde{h}_t$ is regarded as a candidate vector, which is used to control the scale of receiving new input information in the cell state. $\sigma, \tanh$ is the activation function. W_z, W_r, W, W_o is the weight matrix, and $*$ represents the element-wise multiplication.

In the BiGRU neural network, a total of five layers are set up: the input layer, the forward and backward hidden layer, the output layer, and the fully connected layer. The variables selected by the input layer are all the submodalities obtained by decomposing the original time series through VMD, and the target variables selected by the output layer are the labels manually marked in the previous step. The number of neurons in the hidden layer is set to 200. In the training process, the Adam optimizer is used for training, and the values of the parameter learning rate and batch size are 0.0005 and 180, respectively.

Table 3
The time interval corresponding to the data used at each stage.

Stage	Portfolio selecting	Algorithm trading and return calculating
Stage1	2021/01/01–2021/03/31	2021/04/01–2021/06/30
Stage2	2021/04/01–2021/06/30	2021/07/01–2021/09/30
Stage3	2021/07/01–2021/09/30	2021/10/01–2021/12/31
Stage4	2021/10/01–2021/12/31	2022/01/01–2022/03/31
Stage5	2022/01/01–2022/03/31	2022/04/01–2022/06/30

3.7. Algorithmic trading

Based on the daily closing price data and the forecast label generated by BiGRU, this study automatically conducted simulated transactions through an algorithm and calculated the final return value. When the prediction label of day t is “buy”, the model uses all the capital to buy stocks at the closing price; when the prediction label of day t is “sell”, the model sells all stocks at the closing price; when the predicted label for day t is “hold”, the model does not make a trade. When the buy and sell operations are performed, the buyer and seller must bear the corresponding transaction fees. When the transaction amount is less than 5 CNY, the transaction fee is recorded as 5 CNY; when the transaction amount is higher than 5 CNY, the transaction fee is calculated as 0.002 of the transaction amount. Also, the seller in the transaction needs to bear the transaction tax, which is calculated as 0.001 of the transaction amount.

The initial principal of each stock was 10,000 CNY, and the final investment return of the three stocks in the experimental group at the end of stage 1 was evenly distributed to the three stocks in the experimental group in stage 2 as the principal.

4. Data description and experimental details

4.1. Data description

For a closer analysis of portfolios, stock forecasts, and quantitative trading in the new energy stock market, this study divided the entire experimental process into five stages according to time. Each stage included portfolio selection, stock trend forecasting, and algorithmic trading processes. The time intervals for the datasets used in each stage are shown in Table 3.

The data used in this article were provided by the China Stock Market & Accounting Research Database and Choice Database. In the portfolio selection process, this study selected 183 stocks in the new energy concept sector in the Shenzhen Stock Exchange, Shanghai Stock Exchange, and Beijing Stock Exchange for analysis. The monthly return of the stock, the risk-free rate, and the standard deviation of the return between January 2021 and March 2022 were selected as raw data to calculate the Sharpe ratios by quarterly frequency and rank them. In the stock trend forecasting process, for the stocks screened in the previous stage, this study selected five kinds of transaction data, namely opening price, closing price, highest price, lowest price, and trading volume, as raw data to calculate relevant technical indicators and input them into the VMD-BiGRU model. The five kinds of raw transaction data were composed of all data points from January 4, 2010 to June 30, 2022 to predict labeling and quantify transactions. The first 85% of all data points were selected as the training set, and the last 15% were selected as the test set. In the final algorithmic trading and return calculation process, to backtest the value of the stocks selected in the stock screening process, this study conducted algorithmic trading on the selected stocks and calculated the final return value. The time interval of the data was the next interval of the time interval, according to which the Sharpe ratio calculation was based.

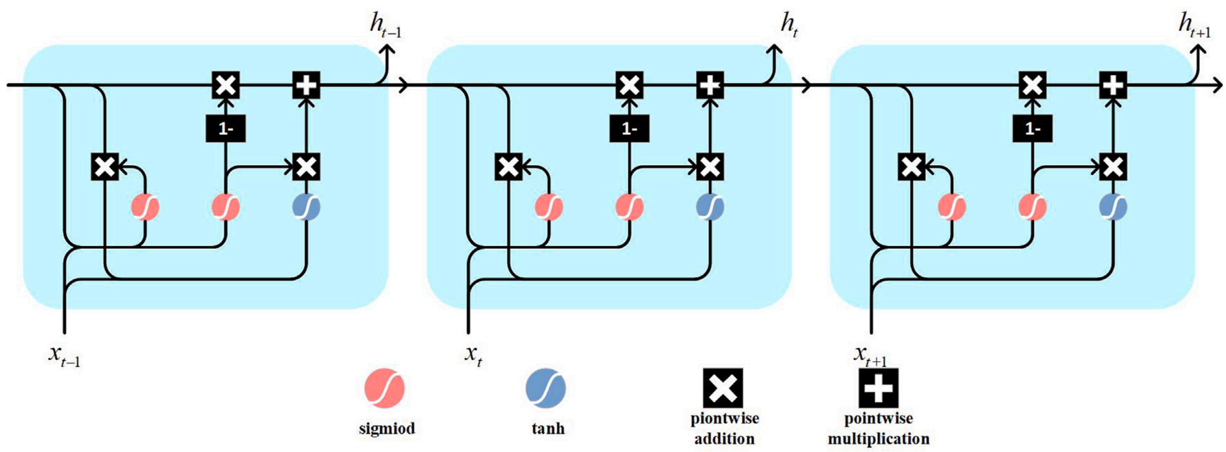

Fig. 3. Architecture of GRU.

Table 4
The portfolio and Sharpe raito in each stage.

Stage	Experimental group			Control group		
Stage1	600744[1.05]	002259[1.04]	000966[1.01]	002547[−0.93]	600580[−0.93]	300427[−1.10]
Stage2	002201[1.51]	002256[1.45]	000009[1.40]	000967[−0.83]	000690[−1.33]	601727[−1.39]
Stage3	000537[2.03]	002411[1.64]	601016[1.56]	600736[−0.52]	002163[−0.71]	000049[−0.92]
Stage4	601137[1.35]	600522[1.26]	600416[1.10]	600290[−0.72]	000009[−0.74]	300082[−0.75]
Stage5	000815[1.40]	002060[0.66]	000683[0.58]	002529[−1.22]	000543[−1.24]	000967[−1.30]

Note: Where the data in [ ] is the Sharpe ratio corresponding to the stock.

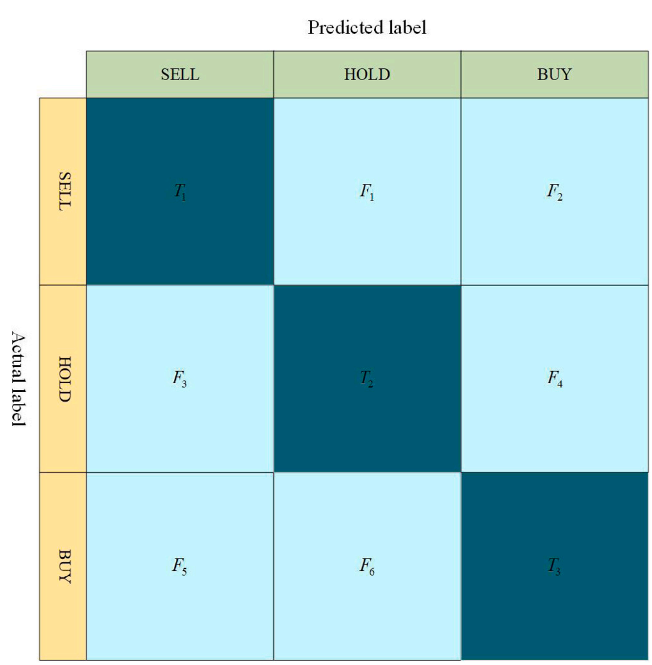

Fig. 4. Confusion matrix structure.

To eliminate the influence of different dimensions and ensure the reliability of the results, this study normalized the original data according to the following formula:

$$\widetilde{X} = \frac{X - \min X}{\max X - \min X} \tag{8}$$

where X and $\widetilde{X}$ represent the data to be normalized and the normalized value, respectively, and $\max X$ and $\min X$ represent the maximum and minimum values of the data, respectively.

4.2. Evaluation index

As shown in Fig. 4, a confusion matrix was introduced to evaluate the accuracy of the BiGRU model predictions. Where T_1, T_2, and T_3 represent the number of correctly predicted "sell", "hold", and "buy" labels, and F_1, F_2, F_3, F_4, F_5, F_6 represent the number of mispredicted labels.

In this paper, accuracy, precision, recall, and F1-score were selected as performance evaluation indicators to analyze the effectiveness of the model. The specific formulas of the four indicators are as follows:

$$Accuracy = \frac{\sum_{i=1}^{3} T_i}{\sum_{i=1}^{3} T_i + \sum_{j=1}^{6} F_j} \tag{9}$$

$$Precision = \frac{T_1}{T_1 + F_3 + F_5} \tag{10}$$

$$Recall = \frac{T_1}{T_1 + F_1 + F_2} \tag{11}$$

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{12}$$

5. Results

5.1. Portfolio selection

Table 4 shows the codes and Sharpe ratios of the selected stocks. The Sharpe ratio reflects the excess return an investor earns per unit of risk. A better Sharpe ratio tends to imply a higher return on a portfolio or a lower level of risk, while a negative Sharpe ratio indicates a portfolio that has a lower return than the risk-free rate. As shown in Table 4, in stage 1, the Sharpe ratios of three stocks, "600744", "002259", and "000966", in the experimental group were 1.05, 1.04, and 1.01, respectively, which were all at a higher level, indicating that these stocks can obtain higher returns under the same risk level. The Sharpe ratios of three stocks, "002547", "600580", and "300427", in the control group were −0.93, −0.93, and −1.10, respectively, which were all less than 0, indicating that the return rate of these stocks was lower than the risk-free rate in stage 1. The stocks in the experimental

Table 5
Analysis of technical indicators of “600744”.

	Mean	Standard deviation	Skewness	Kurtosis	ADF	*P*-value
OP_t	4.54051	1.88162	1.60677	3.55303	−2.26827	0.18240
HI_t	4.64801	1.97228	1.66647	3.68248	−2.21765	0.19990
LO_t	4.44991	1.81000	1.52880	3.16362	−2.19257	0.20895
CL_t	4.55175	1.89397	1.59985	3.41330	−2.24549	0.19015
VO_t	22217571.70089	38979423.25401	4.30223	23.67883	−3.42738	0.01006
R_t	−0.00006	0.03048	0.15550	2.98749	−12.39944	0.00000
$VOL(x)_t$	0.02472	0.01702	1.54191	2.61848	−4.84365	0.00004
R_{1t}	0.02095	0.02398	2.24706	6.31824	−6.64088	0.00000
R_{2t}	0.02089	0.04041	1.14822	5.45938	−7.44130	0.00000
R_{3t}	0.02083	0.05257	1.13758	6.48202	−15.62000	0.00000
R_{4t}	0.02083	0.05257	1.13752	6.48310	−15.62289	0.00000
R_{5t}	0.03933	0.02814	1.76849	3.65949	−4.60689	0.00013
$MTM(x)_t$	−0.00147	0.45547	−0.64812	25.38845	−12.75588	0.00000
$RSI(x)_t$	48.85517	27.13969	0.02352	−0.93761	−13.13587	0.00000
$ATR(x)_t$	0.20808	0.21390	2.89370	9.39730	−3.17332	0.02158
$MA(x)_t$	4.55236	1.88587	1.56952	3.21849	−2.13552	0.23047
$LL(x)_t$	4.31448	1.69063	1.38663	2.60198	−2.09439	0.24678
$HH(x)_t$	4.81430	2.11259	1.76215	3.98308	−2.40166	0.14127
$ROC(x)_t$	100.23927	7.52072	1.74473	11.66340	−11.11571	0.00000
$BIAS$	−0.00012	0.04414	−0.32158	20.73243	−12.31883	0.00000

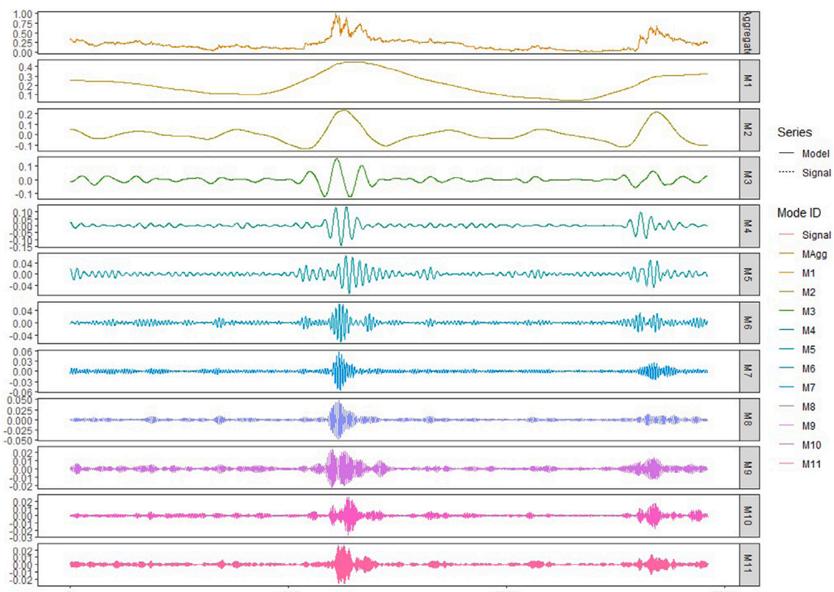

Fig. 5. Closing price.

and control groups in the other stages exhibited similar characteristics to those in stage 1.

We also found that the Sharpe ratio at each stage was not static but varied greatly, reflecting the high volatility of the new energy stock market. As shown in Table 4, the top-ranked stocks in the stage 1 stock pool were “600744”, “002259”, and “000966”, while the top-ranked stocks in stage 2 were “002201”, “002256”, and “000009.” The three stocks with the best ranking in stage 1 were not selected as part of the experimental group in stage 2, which indicates that, in different time periods, the return rate and volatility of stocks may change greatly, causing a change in Sharpe ratio and affecting the ranking. Another important phenomenon we found was that, although the recalculation of the Sharpe ratio at each stage led to a huge change in the ranking, which changed the portfolios of the experimental and control groups, some stocks were in the top position many times due to the stable realization, and some stocks in an experimental group were selected to form part of the control group at different stages as their Sharpe ratio performance was unstable due to changes in yield or volatility. For example, “000967” was selected as part of the control group in both stage 2 and stage 5 and has a negative Sharpe ratio, meaning that the stock may be in a bad long-term yield situation. However, “000009” was selected as part of the experimental group in stage 2 but of the control group in stage 4, indicating that the return or volatility of the stock changed greatly in the time interval between stages 2 and 4.

5.2. Analysis of technical indicators

Table 5 shows the mean, standard deviation, skewness, kurtosis, and ADF test results of the raw data and technical indicator data of stock “600744”. As shown, the mean and standard deviation of the closing price for stock “600744” were 4.55 and 1.89, respectively. The skewness values of $MTM(x)_t$ and $BIAS$ were −0.65 and −0.32, respectively, indicating that these two indicators were left-skewed, while the other indicators were right-skewed. The kurtosis values for VO_t and $MTM(x)_t$ were 23.68 and 25.39, respectively, implying that the data distribution for these two indicators was steeper than the normal distribution. In addition, OP_t, HI_t, LO_t, CL_t, $MA(x)_t$, $LL(x)_t$, and $HH(x)_t$ are considered nonstationary time series because the *P*-values of their ADF tests were all greater than 0.05. These results further corroborate the nonlinear characteristics of time series data in the new energy stock market.

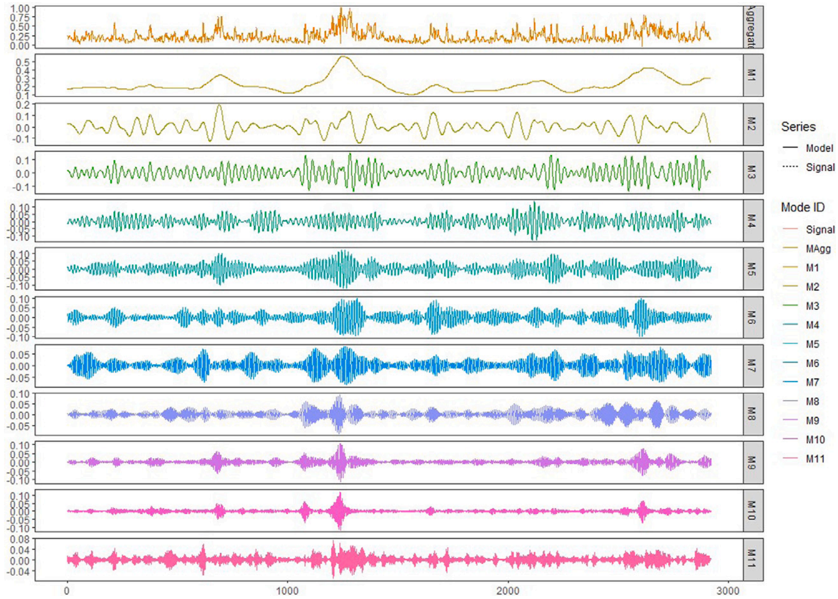

Fig. 6. Volatility.

Table 6
Confusion matrix of different models.

		1-step length			3-step length			5-step length			7-step length		
		Sell	Hold	Buy	Sell	Hold	Buy	Sell	Hold	Buy	Sell	Hold	Buy
	Sell	16	114	0	9	121	0	17	113	0	7	95	27
LSTM	Hold	11	170	0	8	173	0	16	165	0	6	139	36
	Buy	10	117	0	6	121	0	16	111	0	3	95	29
	Sell	22	108	0	1	116	13	40	90	0	10	116	3
GRU	Hold	27	154	0	0	161	20	62	117	2	15	164	2
	Buy	16	111	0	0	110	17	44	82	1	10	117	0
	Sell	73	35	22	82	31	17	85	27	18	86	34	9
VMD-LSTM	Hold	37	97	47	35	105	41	41	94	46	32	97	52
	Buy	9	36	82	8	29	90	11	28	88	8	30	89
	Sell	72	36	22	97	17	16	78	41	11	83	36	10
VMD-GRU	Hold	41	96	44	36	106	37	29	110	42	26	116	39
	Buy	11	36	80	9	29	89	6	35	86	9	37	81
	Sell	72	37	21	83	28	19	75	45	10	92	29	8
VMD-BiLSTM	Hold	33	105	43	31	107	43	40	105	36	35	99	47
	Buy	9	38	80	7	37	83	5	40	82	11	35	81
	Sell	74	35	21	87	26	17	90	35	5	94	27	8
VMD-BiGRU	Hold	32	100	49	25	117	39	40	104	37	33	109	39
	Buy	8	37	82	5	34	88	14	28	85	8	35	84

5.3. Analysis of VMD decomposition results

Fig. 5 and Fig. 6 show the decomposition results of the closing price and volatility of stock "600744" through VMD. The closing price and volatility series were decomposed into 11 submodalities from low frequency to high frequency, denoted by $M1$–$M11$, respectively, and each submodality represents a volatility factor in the time series. Among all submodalities, $M1$ had the lowest signal frequency, which reflects the long-term trend of closing prices and volatility, $M2$ reflects the seasonal factors of time series changes, and $M3$–$M11$ had a higher frequency, reflecting random walk characteristics of closing price and volatility.

5.4. Model prediction performance

After VMD decomposition of complex, nonstationary raw time series and technical indicators of portfolios in the new energy stock market, input variables were selected and fed into the forecasting model to predict "sell", "hold", and "buy" labels. In this part, to compare the prediction performance of different prediction models and explore the impact of the introduction of VMD and bidirectional neural networks on the model's prediction performance, we chose LSTM, GRU, VMD-LSTM, VMD-GRU, VMD-BiLSTM, and VMD-BiGRU for experimentation and to evaluate prediction accuracy. Of these, in the LSTM and GRU models, we selected a total of 20 indicators, including original data and technical indicators (before decomposition), as input variables; in the VMD-LSTM and VMD-GRU models, we selected the submodal sequence after VMD decomposition as the input variables, representing the introduction of the VMD model and constructing a one-way neural network; in the VMD-BiLSTM and VMD-BiGRU models, we selected the submodal sequences decomposed by VMD as input variables and built a two-way RNN to predict labels. We also compared the prediction accuracy of each model at step lengths 1, 3, 5, and 7.

Table 6 and Table 7 show the confusion matrix and model accuracy of the prediction results of different prediction models under different step lengths. The longitudinal analysis of the two tables implies a comparison of the performance of different prediction models, while the transverse analysis shows the prediction results of the same model under the conditions of step lengths 1, 3, 5, and 7. This study specifically analyzed the confusion matrix of the prediction results of the GRU model when the step length was 3. As shown in Table 6, in the confusion matrix, there were 130 data items whose true label was

Table 7
The performance of different models.

		1-step length			3-step length			5-step length			7-step length		
		Pre	Rec	F1	Pre	Rec	F1	Pre	Rec	F1	Pre	Rec	F1
LSTM	Sell	0.43	0.12	0.19	0.39	0.07	0.12	0.35	0.13	0.19	0.44	0.05	0.10
	Hold	0.42	0.95	0.58	0.42	0.96	0.58	0.42	0.91	0.58	0.42	0.77	0.55
	Buy	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.32	0.23	0.26
	Avg	**0.29**	**0.35**	**0.26**	**0.27**	**0.34**	**0.23**	**0.26**	**0.35**	**0.26**	**0.39**	**0.35**	**0.30**
GRU	Sell	0.34	0.17	0.23	1.00	0.01	0.02	0.27	0.31	0.29	0.29	0.08	0.12
	Hold	0.41	0.85	0.56	0.42	0.89	0.57	0.40	0.65	0.50	0.41	0.91	0.57
	Buy	0.00	0.00	0.00	0.34	0.13	0.19	0.33	0.01	0.02	0.00	0.00	0.00
	Avg	**0.25**	**0.34**	**0.26**	**0.59**	**0.34**	**0.26**	**0.34**	**0.32**	**0.27**	**0.23**	**0.33**	**0.23**
VMD-LSTM	Sell	0.61	0.56	0.59	0.66	0.63	0.64	0.62	0.65	0.64	0.68	0.67	0.67
	Hold	0.58	0.54	0.56	0.64	0.58	0.61	0.63	0.52	0.57	0.60	0.54	0.57
	Buy	0.54	0.65	0.59	0.61	0.71	0.65	0.58	0.69	0.63	0.59	0.70	0.64
	Avg	**0.58**	**0.58**	**0.58**	**0.63**	**0.64**	**0.63**	**0.61**	**0.62**	**0.61**	**0.63**	**0.63**	**0.63**
VMD-GRU	Sell	0.58	0.55	0.57	0.68	0.75	0.71	0.69	0.60	0.64	0.70	0.64	0.67
	Hold	0.57	0.53	0.55	0.70	0.59	0.64	0.59	0.61	0.60	0.61	0.64	0.63
	Buy	0.55	0.63	0.59	0.62	0.70	0.66	0.62	0.68	0.65	0.62	0.64	0.63
	Avg	**0.57**	**0.57**	**0.57**	**0.67**	**0.68**	**0.67**	**0.63**	**0.63**	**0.63**	**0.65**	**0.64**	**0.64**
VMD-BiLSTM	Sell	0.63	0.55	0.59	0.69	0.64	0.66	0.62	0.58	0.60	0.67	0.71	0.69
	Hold	0.58	0.58	0.58	0.62	0.59	0.61	0.55	0.58	0.57	0.61	0.55	0.58
	Buy	0.56	0.63	0.59	0.57	0.65	0.61	0.64	0.65	0.64	0.60	0.64	0.62
	Avg	**0.59**	**0.59**	**0.59**	**0.63**	**0.63**	**0.63**	**0.61**	**0.60**	**0.60**	**0.62**	**0.63**	**0.63**
VMD-BiGRU	Sell	0.65	0.57	0.61	0.74	0.67	0.70	0.62	0.69	0.66	0.70	0.73	0.71
	Hold	0.58	0.55	0.57	0.66	0.65	0.65	0.62	0.57	0.60	0.64	0.60	0.62
	Buy	0.54	0.65	0.59	0.61	0.69	0.65	0.67	0.67	0.67	0.64	0.66	0.65
	Avg	**0.59**	**0.59**	**0.59**	**0.67**	**0.67**	**0.67**	**0.64**	**0.65**	**0.64**	**0.66**	**0.66**	**0.66**

Note: Where pre refers to the precision, rec refers to recall and F1 refers to F1-score of different models. The table above shows the prediction results of the model for stock "600744" as an example.

Table 8
The return of individual stock, experimental group and control group in different stages.

	Stock1	Stock2	Stock3	Experimental group	Stock1	Stock2	Stock3	Control group
Stage1	600744	002259	000966		002547	600580	600192	
	[27036.5]	[12957.3]	[26848.2]	[66842.0]	[15588.7]	[11842.5]	[13634.2]	[41065.4]
Stage2	002201	002256	000009		000967	000690	601727	
	[46004.8]	[84311.8]	[67669.2]	[197985.7]	[16970.4]	[22866.1]	[27507.2]	[67343.7]
Stage3	000537	002411	601016		600736	002163	000049	
	[171207.6]	[102999.2]	[92078.5]	[366285.2]	[26643.7]	[26193.2]	[70023.3]	[122860.2]
Stage4	601137	600522	600416		600290	000009	300082	
	[167079.1]	[220343.1]	[177516.3]	[564938.5]	[53933.0]	[60801.9]	[62619.4]	[177354.3]
Stage5	000815	002060	000683		002529	000543	000967	
	[244640.5]	[364001.4]	[339493.1]	[948135.0]	[77197.2]	[75984.5]	[79343.0]	[232524.7]

Note: Where the data in [ ] is the return corresponding to the stock and portfolio.

"sell", but only one data item was accurately predicted as "sell" by the model, 116 items were incorrectly predicted as "hold", and 13 were mispredicted as "buy". Among the 181 data centers with the true label "hold", 161 were correctly predicted, while 20 were incorrectly classified by the model as "buy". Of the 127 data with the true label "buy", 110 were incorrectly predicted by the model as "hold", and only 17 were accurately predicted. Thus, we found that many "buy" and "sell" labels were incorrectly predicted by the model as "hold" labels, indicating that the model performed poorly in identifying valid "buy" and "sell" opportunities. Also, as shown in Table 7, when the step length was 3, the precision, recall, and F1-score of the GRU model were 0.59, 0.34, and 0.26, respectively, and the precision, recall, and F1-score of the LSTM model, of 0.27, 0.34, and 0.23, respectively, were low. More importantly, the precision, recall, and F1-scores of the LSTM and GRU models in the remaining step lengths were all below 50%. Low levels of precision, recall, and F1-scores indicate that a single GRU and LSTM model cannot make accurate predictions on data labels.

When we input raw unprocessed data and technical indicators into the neural network, the model does not learn the deeper features of the data and make accurate predictions, so the input variables are often considered for preprocessing and feature extraction before being input into the model. The prediction results prove that the introduction of the VMD model greatly improved model performance. When we selected the submodal time series obtained after VMD decomposition as the input variable in the GRU model with step length 3, the precision, recall, and F1-score of the model were 0.67, 0.68, and 0.67, respectively, which were 13.56%, 100.00%, and 157.69% higher than the precision, recall, and F1-score of a single GRU model with the same step length. Comparing the LSTM and VMD-LSTM models with step length 3, we found that the precision, recall, and F1-score of the model were improved by 133.33%, 88.24%, and 173.91%, respectively. The above data show that through the decomposition of the original data by VMD, the prediction model can learn more data features from the decomposed data and make more accurate predictions.

Also, as Zhu et al. (2019) observed, current stock price not only reflects historical information but is the basis of future price status, so the stock price time series has a two-way sequential relationship. Therefore, based on VMD-GRU and VMD-LSTM, we used a bidirectional recurrent neural network and analyzed the variation in model accuracy. As shown in Table 7, the performance of VMD-BiGRU with step length 7 was 0.01, 0.02, and 0.02 higher than that of VMD-GRU in precision, recall, and F1-score, respectively. However, when the step length was 1, there was no significant difference in the prediction performance of the VMD-BiGRU and VMD-GRU models. Also, the precision, recall, and F1-scores of the VMD-BiLSTM and VMD-LSTM models under the same step length were also found to be insignificant (Zhu et al., 2019) believed that the bidirectional neural network time series regression fitting can improve the model performance, but this study found that the introduction of the bidirectional neural network plays a limited role in improving the prediction performance of the model classification.

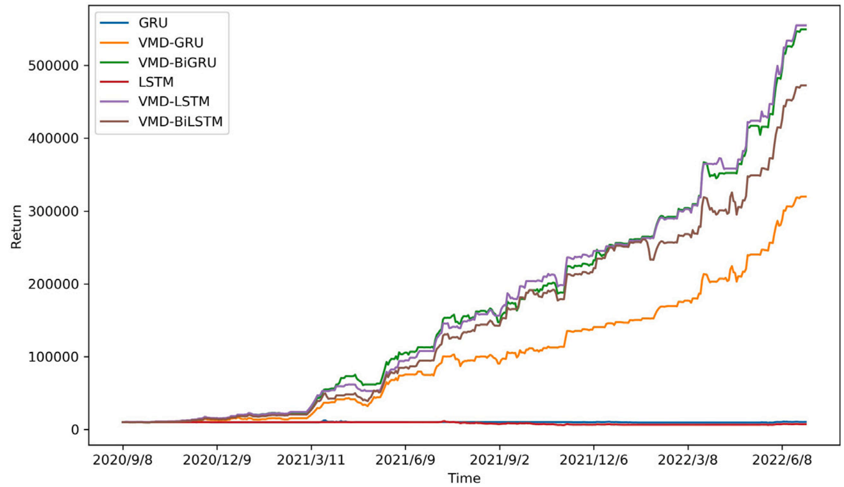

Fig. 7. Returns under different prediction models.

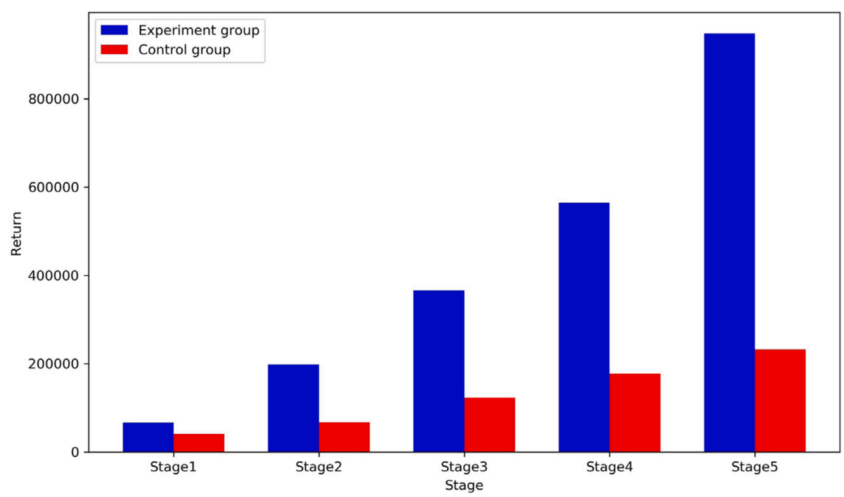

Fig. 8. Return in different stages.

We also found that when the step length was 3, 5, and 7, the prediction performance of the VMD-GRU model was better than that of the VMD-LSTM model under the same step length, and the prediction performance of the VMD-BiGRU model was better than that of the VMD-BiLSTM model. Finally, the effect of step length on model prediction performance was further investigated. For the VMD-BiGRU model, when the step length was 3, the precision, recall, and F1-score of the model were the highest, all 0.67, and when the step length was 1, the model had the lowest accuracy. The VMD-LSTM model also achieved the best performance with a step length of 3.

5.5. Algorithmic trading and revenue calculation

In this part, we first conducted algorithmic trading based on the tags obtained by each prediction model and then calculated and compared the final return value. Fig. 7 shows the returns of our algorithmic trading of stock “600744” from September 7, 2020 to June 29, 2022, based on the label of the six prediction models (the step length was set to 3).

As shown in Fig. 7, when the algorithm trades based on the labels were predicted by the GRU and LSTM models, the final gains were the lowest, at 10411.0 CNY and 7253.6 CNY, respectively. This may be because GRU and LSTM cannot accurately predict “sell”, “buy”, and “hold” labels and thus make incorrect trading decisions, resulting in lower returns. The yield curves of the VMD-BiGRU and VMD-LSTM models fit closely and were at a relatively high level, with their final yields of 549,492.7 CNY and 554,776.6 CNY, respectively. Further, by comparing the prediction accuracy and return results of different models, we found that when the model’s accuracy was much lower than that of other models, its return results were also much lower than those of other models (GRU and BiGRU); however, when the model’s prediction accuracy was slightly lower than that of other models, the future return results could also exceed those of other models (VMD-LSTM and VMD-BiGRU). That is to say, we believe that the accuracy of the prediction model is not completely positively correlated with the final return. Specifically, model accuracy simply reflects the proportion of labels for which the model made correct predictions; however, when trading algorithmically, each label is of different importance to the final return. This may depend on the volatility of the stock price. When stock price volatility is high, predicting the correctness of labels and trading decisions may have a greater impact on earnings values. Since the VMD-BiGRU model performed well in both the accuracy level and the final return, this study selected the VMD-BiGRU model with a step length of 3 for the next analysis.

Next, this study simulated trading in each stock selected in step 1 using the VMD-BiGRU model with a step length of 3 and calculated the returns of individual stocks and stock portfolios at each stage. Table 8 and Fig. 8 show the returns of individual stocks and portfolios at different stages. As shown in Table 8, the final investment returns for the experimental and control groups were 948,135.0 CNY and 232,524.7

CNY, respectively, over the five stages. Moreover, as Fig. 8 shows, we found that the return of the experimental group was greater than that of the control group at each stage, and the difference between the returns of the two portfolios gradually increased over time. As Table 8 shows, the difference between the experimental and control groups increased to 130,642.0 CNY at stage 2 and to 715,610.3 CNY at stage 5. The above results demonstrate the effectiveness of the portfolio strategy proposed in this paper and that the experimental group selected based on the Sharpe ratio ranking outperformed the control group in terms of return.

We further analyzed the returns of individual new energy stocks in the portfolio. We found that although the investment returns of the experimental group were higher than those of the control group at each stage, not every stock in the experimental group had higher returns than each stock in the control group. Although some new energy stocks were selected in the experimental group because of their high Sharpe ratios, they still exhibited a poor return profile. Therefore, we inferred that the relationship between stock returns and the Sharpe ratio was not perfectly positive. When the Sharpe ratio of a stock is higher, the stock has a higher probability of earning a good investment return at the same risk, but it still has the possibility of earning a lower investment return. Taking stage 1 as an example, with the same initial principal amount, the returns of stocks "600744" and "000966" in the experimental group were much higher than those of the three stocks in the control group. However, the return of "002256" in the experimental group was only 12,957.3 CNY, which was lower than that of "002547" and "600192" in the control group by 15,588.7 and 13,634.2 CNY, respectively.

Also, the amount of investment return for each stock was determined by both the initial principal and the stock performance at each stage. In this study, the returns of each stage were accumulated in layers, and the investment returns of the final stage of the experimental and control groups included the joint contribution of all stocks in all stages to the returns. Therefore, the higher the final return of the previous stage, the higher the principal of the current stage, and the higher the return of the portfolio was likely to be. If the principal amount is higher and the stock earns less return in the new period, then the stock is considered to have a lower investment value; if the principal amount is lower and the stock earns more return in the new period, then the stock is considered to have a higher investment value. For example, the initial principal of the control group in stage 3 was 22,447.9 CNY, but the stock "000049" had a return of 70,023.3 CNY at this stage, with a return of 211.94%, which proves that the high stock had a very high value.

Finally, during the portfolio selection process, we found that the stock "000967" had a relatively stable level of investment return and risk, and therefore, its Sharpe ratio ranking was stable; hence, it was consistently selected for the control group. During the quantitative trading stage, the stock "000967" had returns of 16,970.4 CNY and 79,343.0 CNY in stages 2 and 5, respectively, which were both low levels. The persistent bad performance of stock "000967" in terms of Sharpe ratio and simulated trading returns suggests that the stock may have low investment value and validates the stock momentum effect that stocks with high returns in the past have a higher probability of achieving high returns in the future. Stock "000009" was selected for the experimental group in stage 2, with a return of 67,669.2 CNY, and for the control group in stage 4, with a return of 60,801.9 CNY. The large changes in the Sharpe ratio and returns of stock "000009" over a short period of time imply that the stock had a high volatility and risk, which validates its reversal effect: a stock with a high return in the past has a low probability of obtaining a high return in the future.

6. Discussion

6.1. Results summary and discussion

Time series in financial markets are nonstationary, nonsmooth, and nonlinear (Zhou et al., 2019; Shi et al., 2021; de Lima e Silva et al., 2020), as illustrated by the data results in Section 5.2. Compared to other stock markets, the new energy stock market has a higher degree of industry emergence, which further enhances volatility and risk (Salisu and Adediran, 2020; Dutta et al., 2020). Therefore, portfolio selection and trend forecasting become more difficult in the new energy finance market, leaving investors facing greater challenges. We therefore explored three specific questions: (1) how to choose a robust, high-yield, low risk portfolio, (2) how to accurately predict future trends in a portfolio, and (3) how to trade efficiently. Then, this study built a complex quantitative system that integrated portfolio selection, portfolio trend forecasting, and algorithmic trading to cope with investment decisions in the new energy investment market.

With the same investment capital, forecasting model, and trading strategy, the experimental group had four times the return of the control group over 15 months, which proves that portfolio selection is the most important part of investment decisions, and that the Sharpe ratio can, indeed, reflect the return and risk of an investment portfolio. However, we also found that although the experimental group performed better than the control group in terms of return on investment at each stage, not all stocks in the experimental group performed better than those in the control group. This shows that despite the consideration of both return and risk, the Sharpe ratio has limitations, and we cannot rely on it to assess the future value of a portfolio. For example, Ponzi schemes had very high empirical Sharpe ratios before they failed and were exposed. Sharpe ratios are susceptible to statistical characteristics inherent in portfolios, such as nonnormality (Zakamouline and Koekebakker, 2009). The Sharpe ratio performs better in measuring portfolio performance when returns are normally distributed; however, the distribution of numerous portfolio returns deviates from the normal distribution when the Sharpe ratio may lead to misleading conclusions (Wang et al., 2022a). Also, Sharpe ratios are believed to be manipulated through various strategies, such as changing the shape of the return distribution (Bailey et al., 2012). Static observation of the Sharpe ratio results obtained by long-period and low frequency calculations can further exacerbate the above problems, while high frequency calculations and continuous updates of the Sharpe ratios facilitate avoiding the above problems and finding better portfolio frontiers and diversifying risks.

In different time stages, the Sharpe ratio of the investment portfolio is not stable and unchanged; often, there will be a large degree of volatility. It is common for stocks with a high Sharpe ratio and top ranking at this stage to have a sharp decline in Sharpe ratio within three months, one month, or less, and rank last. This proves the nonrobustness of the Sharpe ratio of the portfolio. Kim and Kim (2018) and Bai et al. (2019) focused on statically observing the mean and variance of a certain moment in selecting a portfolio, which solves the optimal portfolio selection problem at that moment. As Gargallo et al. (2022) discussed, we also believe that dynamic analysis of Sharpe ratios and continuous portfolio adjustment are essential to reduce and diversify the risks associated with market changes and achieve optimal portfolio diversification. Considering the computational complexity of the model, we chose a three-month period for sequential rolling Sharpe ratio calculation and dynamic portfolio selection according to the company's quarterly reports. Further, we speculated that investors could perform more frequent Sharpe ratio calculations and portfolio adjustments to find the optimal portfolio frontier over time to achieve optimal diversification of portfolio and risk. The dynamic updating of Sharpe ratios and real-time portfolio adjustment will increase the mathematical computational cost, but this is acceptable in relation to the benefits it brings.

The VMD-BiGRU neural network used in this paper performed well in terms of prediction accuracy and return in predicting the trend of portfolios. Financial time series often contain a great deal of noise caused by the market environment and exhibit nonlinear and nonstationary characteristics, resulting in the bad forecasting performance of time series models (Rhif et al., 2019). The single GRU and LSTM models played a limited role in the process of predicting labels, and we further analyzed the reasons for the low accuracy of the model. When predictions are made by a single model based on the original time series and technical index series (before decomposition), we believe that these indicators can only reflect the surface data characteristics and are not enough to reflect the deep characteristics of the data for model learning. This may also be one of the reasons that many studies perform data preprocessing and feature extraction before using machine learning or deep models. Therefore, the introduction of VMD can significantly improve the prediction accuracy of the model, and this finding is consistent with Zhu et al. (2019) and He et al. (2019). With excellent noise immunity and stability, VMD is adept at handling nonstationary and nonlinear data in finance time series by decomposing the original complex time series data into relatively smooth subseries with different frequency scales, which can further reflect the long-term trends, seasonal trends, and stochastic features of the time series (Liu et al., 2021; Chaitanya et al., 2021). Based on the above model, this study investigated whether the addition of a bidirectional neural network would help to improve model performance; however, analysis of the results regrettably showed that the bidirectional neural network made little contribution to model accuracy. This finding is different from that of Zhu et al. (2019), who argued that the financial time series has a bidirectional sequential relationship and therefore bidirectional neural networks are more realistic; their experimental results also show that bidirectional neural networks improve the model fitting performance and trend prediction accuracy.

Finally, high frequency quantitative trading led by computers has been found to deliver high returns. Investors are susceptible to emotional volatility, growth experience, personal characteristics, and other factors in the decision-making process (Oehler et al., 2018; Rao and Zhou, 2019). The high return and high-risk nature of the new energy financial market may further increase the emotional volatility and psychological stress of investors, causing them to miss optimal investment decisions and investment timing. Quantitative trading is based on data and algorithms, which are not affected by subjective factors and can more accurately seize investment opportunities and conduct high frequency trading, bringing investors substantial returns.

6.2. Implications for theory and practice

As an emerging financial market, the new energy stock market is characterized by high volatility and risk, which are reinforced by the volatility of traditional energy financial markets, the instability of the international political environment, and the occurrence of extreme events. To enable investors to diversify risk and obtain more consistent high returns, we built a complex financial trading system that combines portfolio selection, trend forecasting, and quantitative trading.

First, due to the nonstability and nonrobustness of the Sharpe ratio, the system took a sequential, rolling Sharpe ratio calculation and dynamically selected portfolios to reduce risk from market changes and achieve optimal portfolio diversification. The portfolios selected by the system proved to have high returns, demonstrating the excellent stock selection ability of the system and reflecting the importance of the rolling Sharpe ratio in portfolio returns and risks.

Second, the VMD-BiGRU model was introduced to predict the portfolio's trend forecast. The model was shown to improve forecasting performance to a large extent compared to the single-model GRU and LSTM, since, with the data decomposed by VMD, the model was able to learn deeper features to make more accurate forecasts.

Based on the model's prediction results, we quantified the trades of the portfolios and compared their returns. In the highly sensitive, volatile, and risky new energy equity market, quantitative trading can further take advantage of avoiding the influence of investor sentiment and other subjective factors to accurately capture investment opportunities based on large amounts of historical data and trade at high frequencies, thus generating significant high returns.

Finally, the three modules of the system are both independent and collaborative. The system allows investors to identify and adjust the performance of their portfolio at each stage independently. The first module anchors the portfolio range for the last two modules, significantly reducing the system's computational workload. The latter two modules in turn refine the portfolio selected by the first module to test its performance in the real financial markets. Such a system design is more helpful to improve the efficiency of the model operation.

6.3. Limitations and future research

The rapid development of new energy is not only seen in China but also worldwide, where countries are promoting the transition from traditional energy sources to new energy sources and keeping an eye on the performance of listed new energy companies in the capital markets. However, this paper only considered the performance of the quantitative financial trading system in the Chinese new energy stock market, and the performance of the system in other financial markets around the world is still unclear. We speculate that the system can be profitable in other countries' new energy finance markets, but the final profit of the model may vary due to the differences in the development of the new energy finance industry in each country. Further, we could apply this financial investment decision system to other financial investment markets in the world, such as the New York Stock Exchange, National Association of Securities Dealers Automated Quotation, London Stock Exchange, and explore the performance of the system and compare the similarity or difference of the system's investment performance in different financial investment markets.

7. Conclusions

This paper constructs an integrated complex multifunctional financial investment decision system and further investigates the performance of the system in the new energy stock market. The system provides decision-making assistance to investors from three perspectives: portfolio selection, trend forecasting, and quantitative trading. In terms of portfolio selection, this paper reveals that, on the one hand, the Sharpe ratio is an important indicator of portfolio return and risk, and, on the other hand, points out its nonstationarity and nonrobustness. Therefore, instead of looking at the Sharpe ratio of stocks statically, this paper tries to dynamically adjust the portfolio and find the optimal boundaries of the portfolio by calculating the Sharpe ratio of stocks continuously on a rolling basis to achieve high return and risk diversification. In trend prediction, we found that single deep learning models, such as GRU and LSTM, do not learn the deep features of the data, resulting in poor prediction performance, so we must preprocess the input data features by VMD and use composite models such as VMD-LSTM, VMD-GRU, VMD-BiLSTM, and VMD-BiGRU to further improve the prediction performance of the model. Regarding quantitative trading, this paper finds that machine-driven quantitative trading can efficiently capture trading opportunities and trade them promptly, with the advantages of high trading frequency, short position duration, low risk, and high return amount.

CRediT authorship contribution statement

Qing Zhu: Conceptualization, Writing – original draft, Writing – review & editing. **Xiaobo Zhou:** Data curation, Writing – original draft, Writing – review & editing. **Shan Liu:** Project administration, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the National Natural Science Foundation (NSFC) Programs of China [72032006, and 92146005]. We also appreciate the support of the Youth Innovation Team of Shaanxi Universities "Big data and Business Intelligent Innovation Team, China." (No. 21JP067).

References

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., Perez de Gracia, F., 2018. Oil volatility, oil and gas firms and portfolio diversification. Energy Econ. 70, 499–515. http://dx.doi.org/10.1016/j.eneco.2018.01.023.

Arthur, W.B., 2021. Foundations of complexity economics. Nat. Rev. Phys. 3 (2), 136–145. http://dx.doi.org/10.1038/s42254-020-00273-3.

Bai, L., Liu, Y., Wang, Q., Chen, C., 2019. Improving portfolio performance of renewable energy stocks using robust portfolio approach: Evidence from China. Physica A 533, 122059. http://dx.doi.org/10.1016/j.physa.2019.122059.

Bailey, D.H., López de Prado, M., López de Prado, M., 2012. The sharpe ratio efficient frontier. J. Risk 15, 13. http://dx.doi.org/10.2139/ssrn.1821643.

Ben Jabeur, S., Khalfaoui, R., Ben Arfi, W., 2021. The effect of green energy, global environmental indexes, and stock markets in predicting oil price crashes: Evidence from explainable machine learning. J. Environ. Manag. 298, 113511. http://dx.doi.org/10.1016/j.jenvman.2021.113511.

Bloomberg, N.E.F., 2021. New energy outlook 2021-executive summary. Available from: https://About.Bnef.Com/New-Energy-Outlook.

Chaitanya, B., Yadav, A., Pazoki, M., Abdelaziz, A.Y., 2021. Chapter 8 - A comprehensive review of islanding detection methods. In: Zobaa, A.F., Abdel Aleem, S.H. (Eds.), Uncertainties in Modern Power Systems. Academic Press, pp. 211–256. http://dx.doi.org/10.1016/B978-0-12-820491-7.00008-6.

Chen, C., Liu, D., Xian, L., Pan, L., Wang, L., Yang, M., Quan, L., 2020. Best-case scenario robust portfolio for energy stock market. Energy 213, 118664. http://dx.doi.org/10.1016/j.energy.2020.118664.

Cheng, X., Huang, D., Chen, J., Meng, X., Li, C., 2019. An investigation on factors affecting stock valuation using text mining for automated trading. Sustainability 11 (7), 1938. http://dx.doi.org/10.3390/su11071938.

Cho, I., Wesslen, R., Karduni, A., Santhanam, S., Shaikh, S., Dou, W., 2017. The anchoring effect in decision-making with visual analytics. In: 2017 IEEE Conference on Visual Analytics Science and Technology. VAST, pp. 116–126. http://dx.doi.org/10.1109/VAST.2017.8585665.

Chong, E., Han, C., Park, F.C., 2017. Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies. Expert Syst. Appl. 83, 187–205. http://dx.doi.org/10.1016/j.eswa.2017.04.030.

Daniel, K., Hirshleifer, D., 2015. Overconfident investors, predictable returns, and excessive trading. J. Econ. Perspect. 29 (4), 61–88. http://dx.doi.org/10.1257/jep.29.4.61.

de Lima e Silva, P.C., Severiano, C.A., Alves, M.A., Silva, R., Cohen, M.W., Guimarães, F.G., 2020. Forecasting in non-stationary environments with fuzzy time series. Appl. Soft Comput. 97, 106825. http://dx.doi.org/10.1016/j.asoc.2020.106825.

Dragomiretskiy, K., Zosso, D., 2014. Variational mode decomposition. IEEE Trans. Signal Process. 62 (3), 531–544. http://dx.doi.org/10.1109/TSP.2013.2288675.

Dutta, A., 2017. Oil price uncertainty and clean energy stock returns: New evidence from crude oil volatility index. J. Clean. Prod. 164, 1157–1166. http://dx.doi.org/10.1016/j.jclepro.2017.07.050.

Dutta, A., Bouri, E., Saeed, T., Vo, X.V., 2020. Impact of energy sector volatility on clean energy assets. Energy 212, 118657. http://dx.doi.org/10.1016/j.energy.2020.118657.

Elsayed, A.H., Nasreen, S., Tiwari, A.K., 2020. Time-varying co-movements between energy market and global financial markets: Implication for portfolio diversification and hedging strategies. Energy Econ. 90, 104847. http://dx.doi.org/10.1016/j.eneco.2020.104847.

Fan, J., Li, Q., Hou, J., Feng, X., Karimian, H., Lin, S., 2017. A spatiotemporal prediction framework for air pollution based on deep RNN. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. IV-4/W2, 15–22. http://dx.doi.org/10.5194/isprs-annals-IV-4-W2-15-2017.

Gal, D., Rucker, D.D., 2018. The loss of loss aversion: Will it loom larger than its gain? J. Consum. Psychol. 28 (3), 497–516. http://dx.doi.org/10.1002/jcpy.1047.

Gargallo, P., Lample, L., Miguel, J., Salvador, M., 2022. Dynamic comparison of portfolio risk: Clean vs dirty energy. Finance Res. Lett. 47, 102957. http://dx.doi.org/10.1016/j.frl.2022.102957.

Gu, L., Feng, C., et al., 2022. Research on stock price prediction based on Markov-LSTM neural network-take the new energy industry as an example. Acad. J. Bus. Manag. 4 (4), http://dx.doi.org/10.25236/AJBM.2022.040408.

He, X., Luo, J., Zuo, G., Xie, J., 2019. Daily runoff forecasting using a hybrid model based on variational mode decomposition and deep neural networks. Water Resour. Manag. 33 (4), 1571–1590. http://dx.doi.org/10.1007/s11269-019-2183-x.

Heaton, J.B., Polson, N.G., Witte, J.H., 2017. Deep learning for finance: Deep portfolios. Appl. Stoch. Models Bus. Ind. 33 (1), 3–12. http://dx.doi.org/10.1002/asmb.2209.

Henrique, B.M., Sobreiro, V.A., Kimura, H., 2019. Literature review: Machine learning techniques applied to financial market prediction. Expert Syst. Appl. 124, 226–251. http://dx.doi.org/10.1016/j.eswa.2019.01.012.

Hochreiter, S., Schmidhuber, J., 1997. Long short-term memory. Neural Comput. 9 (8), 1735–1780. http://dx.doi.org/10.1162/neco.1997.9.8.1735.

Iyke, B.N., Tran, V.T., Narayan, P.K., 2021. Can energy security predict energy stock returns? Energy Econ. 94, 105052. http://dx.doi.org/10.1016/j.eneco.2020.105052.

Kim, J., Kim, J., 2018. Optimal portfolio for LNG importation in Korea using a two-step portfolio model and a fuzzy analytic hierarchy process. Energies 11, 3049. http://dx.doi.org/10.3390/en11113049.

Koratamaddi, P., Wadhwani, K., Gupta, M., Sanjeevi, S.G., 2021. Market sentiment-aware deep reinforcement learning approach for stock portfolio allocation. Eng. Sci. Technol., Int. J. 24 (4), 848–859. http://dx.doi.org/10.1016/j.jestch.2021.01.007.

Lahmiri, S., 2016. A variational mode decompoisition approach for analysis and forecasting of economic and financial time series. Expert Syst. Appl. 55, 268–273. http://dx.doi.org/10.1016/j.eswa.2016.02.025.

Li, X., Ma, X., Xiao, F., Xiao, C., Wang, F., Zhang, S., 2022. Time-series production forecasting method based on the integration of bidirectional Gated Recurrent Unit (Bi-GRU) network and sparrow search algorithm (SSA). J. Pet. Sci. Eng. 208, 109309. http://dx.doi.org/10.1016/j.petrol.2021.109309.

Li, Q., Wang, T., Gong, Q., Chen, Y., Lin, Z., kwang Song, S., 2014. Media-aware quantitative trading based on public web information. Decis. Support Syst. 61, 93–105. http://dx.doi.org/10.1016/j.dss.2014.01.013.

Li, X., Wei, Y., 2018. The dependence and risk spillover between crude oil market and China stock market: New evidence from a variational mode decomposition-based copula method. Energy Econ. 74, 565–581. http://dx.doi.org/10.1016/j.eneco.2018.07.011.

Lin, B., Chen, Y., 2019. Dynamic linkages and spillover effects between CET market, coal market and stock market of new energy companies: A case of Beijing CET market in China. Energy 172, 1198–1210. http://dx.doi.org/10.1016/j.energy.2019.02.029.

Liu, Y., Liu, Q., Zhao, H., Pan, Z., Liu, C., 2020. Adaptive quantitative trading: An imitative deep reinforcement learning approach. In: Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34, no. 02. pp. 2128–2135. http://dx.doi.org/10.1609/aaai.v34i02.5587.

Liu, H., Yan, G., Duan, Z., Chen, C., 2021. Intelligent modeling strategies for forecasting air quality time series: A review. Appl. Soft Comput. 102, 106957. http://dx.doi.org/10.1016/j.asoc.2020.106957.

Markowitz, H., 1952. Portfolio selection. J. Finance 7 (1), 77–91.

Mitra, G., Kyriakis, T., Lucas, C., Pirbhad, M., 2003. Chapter 1 - A review of portfolio planning: Models and systems. In: Satchell, S., Scowcroft, A. (Eds.), Advances in Portfolio Construction and Implementation. In: Quantitative Finance, Butterworth-Heinemann, Oxford, pp. 1–39. http://dx.doi.org/10.1016/B978-075065448-7.50002-1.

Nabi, R.L., Walter, N., Oshidary, N., Endacott, C.G., Love-Nichols, J., Lew, Z.J., Aune, A., 2020. Can emotions capture the elusive gain-loss framing effect? A meta-analysis. Commun. Res. 47 (8), 1107–1130. http://dx.doi.org/10.1177/0093650219861256.

Narayan, P.K., 2019. Can stale oil price news predict stock returns? Energy Econ. 83, 430–444. http://dx.doi.org/10.1016/j.eneco.2019.07.022.

Oehler, A., Wendt, S., Wedlich, F., Horn, M., 2018. Investors' personality influences investment decisions: Experimental evidence on extraversion and neuroticism. J. Behav. Finance 19 (1), 30–48. http://dx.doi.org/10.1080/15427560.2017.1366495.

Rao, L., Zhou, L., 2019. The role of stock price synchronicity on the return-sentiment relation. North Am. J. Econ. Finance 47, 119–131. http://dx.doi.org/10.1016/j.najef.2018.12.008.

Rhif, M., Ben Abbes, A., Farah, I.R., Martínez, B., Sang, Y., 2019. Wavelet transform application for/in non-stationary time-series analysis: A review. Appl. Sci. 9 (7), 1345. http://dx.doi.org/10.3390/app9071345.

Sadorsky, P., 2012. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Econ. 34 (1), 248–255. http://dx.doi.org/10.1016/j.eneco.2011.03.006.

Salisu, A., Adediran, I., 2020. Uncertainty due to infectious diseases and energy market volatility. Energy Res. Lett. 1 (2), 14185. http://dx.doi.org/10.46557/001c.14185.

Schuster, M., Paliwal, K., 1997. Bidirectional recurrent neural networks. IEEE Trans. Signal Process. 45 (11), 2673–2681. http://dx.doi.org/10.1109/78.650093.

Sezer, O.B., Ozbayoglu, A.M., 2018. Algorithmic financial trading with deep convolutional neural networks: Time series to image conversion approach. Appl. Soft Comput. 70, 525–538. http://dx.doi.org/10.1016/j.asoc.2018.04.024.

Shah, D., Isah, H., Zulkernine, F., 2019. Stock market analysis: A review and taxonomy of prediction techniques. Int. J. Financ. Stud. 7 (2), 26. http://dx.doi.org/10.3390/ijfs7020026.

Sharpe, W.F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. J. Finance 19 (3), 425–442. http://dx.doi.org/10.1111/j.1540-6261.1964.tb02865.x.

Sharpe, W.F., 1998. The sharpe ratio. Streetwise–Best J. Portfolio Manag. 169–185.

Shi, Z., Bai, Y., Jin, X., Wang, X., Su, T., Kong, J., 2021. Parallel deep prediction with covariance intersection fusion on non-stationary time series. Knowl.-Based Syst. 211, 106523. http://dx.doi.org/10.1016/j.knosys.2020.106523.

Sun, C., Ding, D., Fang, X., Zhang, H., Li, J., 2019. How do fossil energy prices affect the stock prices of new energy companies? Evidence from divisia energy price index in China's market. Energy 169, 637–645. http://dx.doi.org/10.1016/j.energy.2018.12.032.

Ta, V.-D., Liu, C.-M., Tadesse, D.A., 2020. Portfolio optimization-based stock prediction using long-short term memory network in quantitative trading. Appl. Sci. 10 (2), 437. http://dx.doi.org/10.3390/app10020437.

Wang, C.D., Chen, Z., Lian, Y., Chen, M., 2022a. Asset selection based on high frequency sharpe ratio. J. Econometrics 227 (1), 168–188. http://dx.doi.org/10.1016/j.jeconom.2020.05.007.

Wang, Y., Luo, C., 2021. An intelligent quantitative trading system based on intuitionistic-GRU fuzzy neural networks. Appl. Soft Comput. 108, 107471. http://dx.doi.org/10.1016/j.asoc.2021.107471.

Wang, S., Wang, L., Pi, Y., 2022b. A hybrid differential evolution algorithm for a stochastic location-inventory-delivery problem with joint replenishment. Data Sci. Manag. 5 (3), 124–136. http://dx.doi.org/10.1016/j.dsm.2022.07.003.

Wang, L., Wang, S., Yuan, Z., Peng, L., 2021. Analyzing potential tourist behavior using PCA and modified affinity propagation clustering based on Baidu index: Taking Beijing city as an example. Data Sci. Manag. 2, 12–19. http://dx.doi.org/10.1016/j.dsm.2021.05.001.

Wang, M.-X., Xiao, Z., gang Peng, H., kang Wang, X., qiang Wang, J., 2022c. Stock price prediction for new energy vehicle enterprises: An integrated method based on time series and cloud models. Expert Syst. Appl. 208, 118125. http://dx.doi.org/10.1016/j.eswa.2022.118125.

Wen, X., Guo, Y., Wei, Y., Huang, D., 2014. How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China. Energy Econ. 41, 63–75. http://dx.doi.org/10.1016/j.eneco.2013.10.018.

Wu, J., Wang, C., Xiong, L., Sun, H., 2019. Quantitative trading on stock market based on deep reinforcement learning. In: 2019 International Joint Conference on Neural Networks. IJCNN, pp. 1–8. http://dx.doi.org/10.1109/IJCNN.2019.8851831.

Zakamouline, V., Koekebakker, S., 2009. Portfolio performance evaluation with generalized sharpe ratios: Beyond the mean and variance. J. Bank. Financ. 33 (7), 1242–1254. http://dx.doi.org/10.1016/j.jbankfin.2009.01.005.

Zhou, F., min Zhou, H., Yang, Z., Yang, L., 2019. EMD2FNN: A strategy combining empirical mode decomposition and factorization machine based neural network for stock market trend prediction. Expert Syst. Appl. 115, 136–151. http://dx.doi.org/10.1016/j.eswa.2018.07.065.

Zhu, Q., Ruan, Y., Liu, S., Wang, L., 2021. Novel information fusion model for simulating the effect of global public events on the sino-US soybean futures market. Data Sci. Manag. 1 (1), 48–59. http://dx.doi.org/10.1016/j.dsm.2021.02.005.

Zhu, Q., Zhang, F., Liu, S., Li, Y., 2022. An anticrime information support system design: Application of K-means-VMD-BiGRU in the city of Chicago. Inf. Manag. 59 (5), 103247. http://dx.doi.org/10.1016/j.im.2019.103247.

Zhu, Q., Zhang, F., Liu, S., Wu, Y., Wang, L., 2019. A hybrid VMD–BiGRU model for rubber futures time series forecasting. Appl. Soft Comput. 84, 105739. http://dx.doi.org/10.1016/j.asoc.2019.105739.

Zhuang, X.-N., Chen, Z.-Y., Wu, Y.-C., Guo, G.-P., 2022. Quantum computational quantitative trading: High-frequency statistical arbitrage algorithm. New J. Phys. 24 (7), 073036. http://dx.doi.org/10.1088/1367-2630/ac7f26.