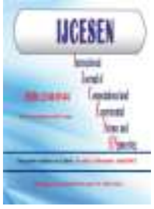
International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.1 (2025) pp. 1096-1107
http://www.ijcesen.com



ISSN: 2149-9144

Research Article

A Study on Asset Pricing in Stock Market Based on Hopfield Neural Network

Tansi Sun*

Olin Business School, Washington University in St. Louis, St. Louis，MO; United States; 63130
* **Corresponding Author Email:** Tansi_sun@163.com - **ORCID:** 0000-0003-4708-95XX

Article Info:

DOI: 10.22399/ijcesen.996
Received : 01 December 2024
Accepted : 05 February 2025

Keywords :

Hopfield neural network,
Learning algorithm,
Predictive modelling,
Stock market.

Abstract:

Nowadays, with globalisation and financial globalisation, stock markets are becoming more and more complex, which cannot be explained by classical financial analysis. In this paper, Hopfield neural network is used to describe the complex nonlinear and asymmetric financial system in detail, and a stock market prediction method is proposed. The specific results are as follows: Hopfield neural network is introduced, and the network structure, operation mode and convergence principle are described in detail. Finally, the performance of FNN is successfully simulated. On the basis of the simulation model, we used the Hopfield neural network based on FSK and applied it to the FSK based on RFE-GSWOA-Hopfield; the MAPE value, the RMSE value, and the MAE value of the model proposed in this paper reached the minimum values in several models, which were 29.206, 0.594,23.131, and the R2 reaches the maximum value of 0.952 in several models. In addition, the experiments also prove that the RFE-GSWOA-Hopfield model is better in prediction efficiency and optimisation accuracy.

1. Introduction

With the development of globalization and globalization of finance, the stock market has become increasingly complex and has revealed a number of anomalies which cannot be accounted for by conventional finance and economics, such as the absence or even complete departure of an ideal market model based on an effective (perfect) market hypothesis. But in the meantime, there are obvious similarities between the classic statistics of finance, for example, stock index, volume price change and fluctuation.

It shows that despite being a complicated finance system, there are likely to be general rules in the sea of data [1]. In recent years, a lot of research has been done on it based on neural network at home and abroad.

After researching and analysing the articles of many scholars on the study of the effectiveness of market vulnerability, Li Junliang [2] found that the traditional research methods generally have various shortcomings such as contingent conclusions of technical analysis, over-exploitation of positive data, lopsided argumentation methods and the problem of joint assumptions brought about by statistical testing methods. Xing Weichen [3] elaborated the relevant concepts and properties of stocks and combined them with relevant forecasting principles for technical analysis, and introduced in detail three methods in technical analysis methods, basic analysis, technical analysis and quantitative analysis.

Cong Ruixue [4] applies radial basis neural network to stock prediction, and takes the closing price of Air China as the research object to carry out simulation experiments, and achieves good prediction effect, which shows that this method has good application and promotion ability.

Ouyang Yulong[5] clarified the development dynamics of China's A-share market by collating the existing literature and stock market information, identified the potential impact factors, and constructed an investor expectation index on the basis of traditional financial analysis to measure investor sentiment. Liu Nan[6] constructed a stock price prediction model based on fully connected neural network and convolutional neural network.

Based on Hopfield neural network, this paper provides a detailed description of classical financial statistical features, proposes a prediction method for the stock market, and verifies the prediction method, It has important realistic meaning and theory value for the prevention of finance risk and regulation of financial market.

2. Hopfield neural network analysis

2.1 Hopfield Neural Network Analysis

Hopdield neural network is a single layer neural network with feedback. The output of each neuron is connected to a neuron that is not its own through connection weights, i.e., the output xi is multiplied by the connection weights and then acted on the jth neuron [7]. Each neuron receives inputs from other neurons and then outputs them after processing by an activation function, which is generally denoted by f_1 f_2 ,.... f_n denotes its state activation function, and θi denotes its threshold function [8]. DHNN generally chooses the same activation function with the following expression:

$$f_1(x) = f_2(x) = \cdots = f_n(x) = sgn(x) = \begin{cases} 1 & x \geq 0 \\ -1 & x < 0 \end{cases} \quad (1)$$

In the above equation, $sgn(x)$ is the sign function.

How the network works

The network generally works in two ways, the asynchronous mode of operation is the most applied, the so-called asynchronous mode of operation is that the network runs with only one neuron i value changing each time, and the values of other neurons remain unchanged, and the state calculation can be carried out according to the following formula [9-11].

$$x_j(t+1) = \begin{cases} sgn\left[\text{net}_j(t)\right] & j = i \\ x_j(t) & j \neq i \end{cases} \quad (2)$$

The changing neurons can be selected in a prescribed order or the order can be determined in a random manner, and the neurons adjust their state each time they do so based on the net positive and negative values of each input to determine whether the state changes this time or not, so not every time a neuron's state changes [12]. The second way is the synchronous way of working, i.e：

$$x_j(t+1) = \text{sgn}\left[\text{net}_j(t)\right] \quad j = 1, 2, \cdots, n \quad (3)$$

Learning algorithms

Artificial neuronal network learning algorithms are generally classified in three ways: δ learning rules, Hebb learning rules, and competitive learning rules.

1) δ learning rule, also known as the corrective learning rule. When the actual output of neuron i at k moments amount, then the amount of error in the：

$$x_j(t+1) = \text{sgn}\left[\text{net}_j(t)\right] \quad j = 1, 2, \cdots, n \quad (4)$$

Then the process of network training can be regarded as the process of finding the minimum, so corrective error learning becomes a typical optimisation problem. Meanwhile the commonly used objective function is to find the minimum of the mean square error, i.e：

$$Y = E\left\{\frac{1}{2}\sum_{i=1}^{N}(t_i - y_i)^2\right\} \quad (5)$$

where E is the statistical expectation operator and Y is the objective function. Since the process of finding the attractor in DHNN network is the process of constantly updating the change of the weight matrix, the above problem can again be transformed into the minimal value of Y to the weight w_{ij}. Then the correction of the weight can be obtained by using the steepest gradient descent method, i.e.:

$$\Delta w_{ij}(k) = \eta \cdot E_i(k) \cdot f'(w_i x) \cdot x_j(k) \quad (6)$$

2) Hebb learning rule

Hebb learning rule that when the neuron states at both ends of a connection right are synchronised then the strength of that connection increases and vice versa decreases, mathematically expressed as [13-15]：

$$\Delta w_j(k) = F(y_i(k), x_i(k)) \quad (7)$$

where， $y_i(k), x_i(k)$ respectively w_g are the states of the neurons at each end, one of the commonly used cases being the：

$$\Delta w_i(k) = \eta \cdot y_i(k) \cdot x_i(k) \quad (8)$$

3) Competitive learning

In this type of learning, the output units of the network compete with each other, and the "winning" unit is the result of the learning, and this unit also inhibits the other units. In this DHNN network, Hebb's learning rule is chosen as the learning algorithm to determine the weights of the DHNN network for the required network size.

2.2 Improvement of Hopfield neural network based on ferroelectric synaptic transistors

Neural network architecture

In this paper, we design a net architecture as illustrated in Figure 1. In this paper, the transfer of electric signal is simulated by nerve signal transfer. Ferroelectric TFT has its source coupled to a neural outlet, and its outlet is coupled to a neuron input section, which receives a modulation voltage pulse from a periphery. In this model, the net is composed of N neurons, which are modeled with 2 ferroelectric MOSFET. Then, a N-N weight matrix is constructed from the ferroelectric synaptic transistors (Figure 1). The network is computed synchronously [16].

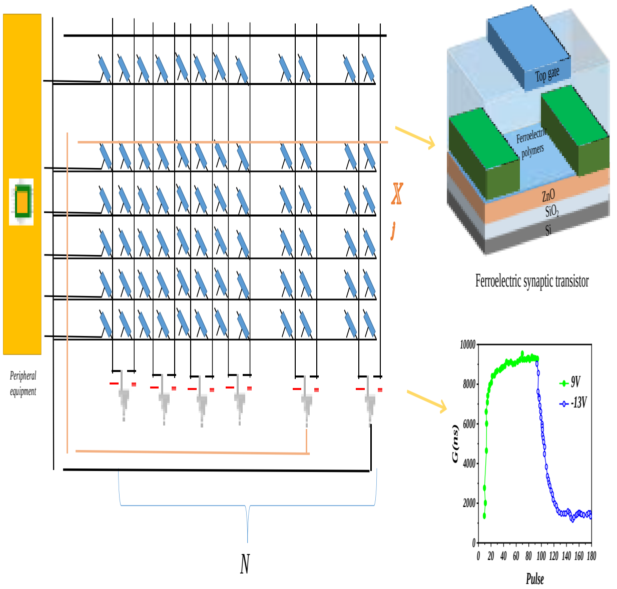


***Figure 1.** Neural network structure.*

Hopfield neural networks can be classified into two types according to the neuron output range. The neuron output ranges of both networks are uniformly set to [0, 1] or [-1, 1], respectively. In the neural network built in this work, a negative neuron output value is simulated by a neuron outputting a negative voltage pulse.

In the synaptic weight pre-programming stage, the weight matrix is artificially designed for the specific function to be achieved or the specific problem to be solved, after which the peripheral device calculates the closest approximate weight that can be achieved for each synapse as well as the applied pulse scheme based on the pre-designed weight matrix based on the mathematical model of synaptic weight regulation and imposes pulses to achieve the conductance regulation through the application of pulses on the third end of each ferroelectric synaptic transistor [17-19].

Synaptic model

In ferroelectric synaptic transistors, the channel conductance can be modulated by the state of polarisation in the ferroelectric gate dielectric, which, according to ferroelectric domain dynamics, can be precisely controlled in the ferroelectric gate dielectric layer by varying the amplitude/duration/amount of the applied voltage pulses, etc [20]. As an example, the channel conductance (synaptic weights) in a ferroelectric synaptic transistor can be plasticly modulated by voltage pulses applied to the gate, with higher electric field amplitudes producing faster modulation of the channel conductance (Figure 2).

In this paper, the synaptic device model is derived from the ferroelectric synaptic transistors. In this paper, the ferroelectric MOSFET using zinc oxide (ZnO) as the channel, and the ferroelectrics (VDFTrFE) as the ferroelectrics are fabricated (Figure 2)[21-23].

Using the channel conductance as the synaptic weights and by fitting the evolution of the channel conductance under the gate pulse voltage modulation, an approximate analytical expression of the enhanced regulation curve of the synaptic weights in the ferroelectric synaptic transistor neural network is obtained in this work：

$$y = 230.608 - 273.063 \times exp(- x/609.483) \qquad (9)$$

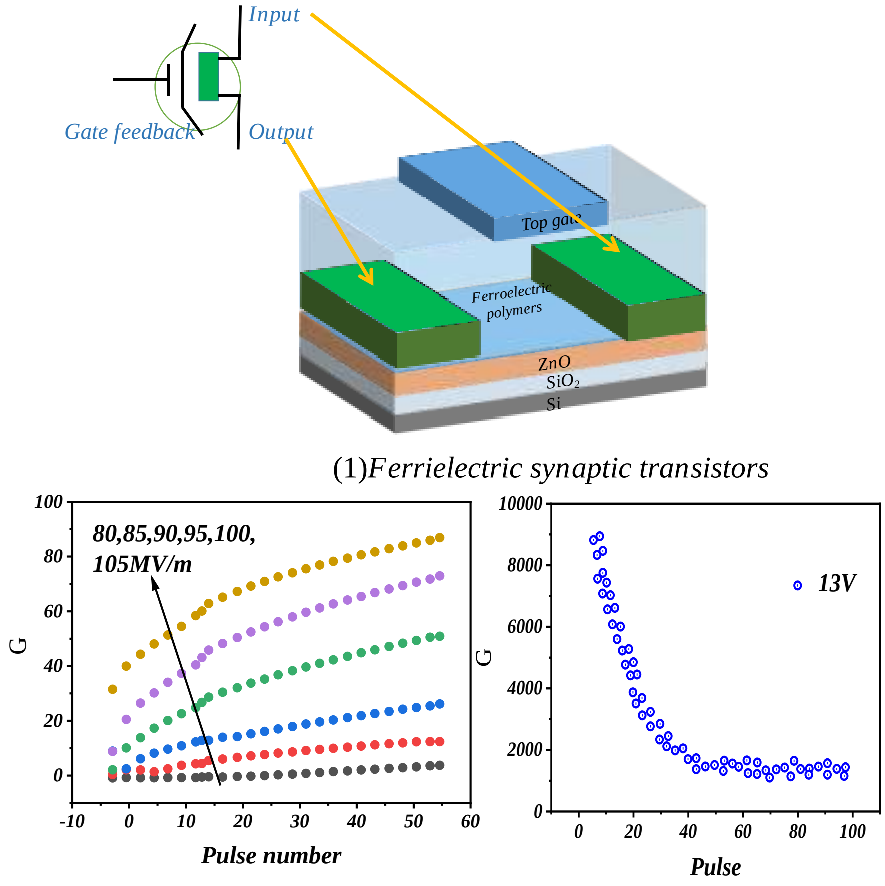
Based on (9), the formula for regulating the conductance increase in the subsequent software simulation model is expressed as follows：

$$b = -609.483 \times ln[- (183.36 \times x - 230.608)/ 237.063]. \qquad (10)$$

$$b = b + \alpha_0 \qquad (11)$$

$$y = \left[-273.063 \times exp\left(-\frac{b}{609.483}\right) + 230.608\right]/183.36 \qquad (12)$$

where the input parameters x_1 and x_2 output parameters represent the conductance before and after regulation, respectively. Equations 9-12 reflect the conductance regulation behaviour of ferroelectric synaptic transistors. All the conductance enhancement operations during the subsequent neural network model simulation are simulated based on this equation. When combining the simulated annealing strategy for the optimal solution of the problem, transient chaos needs to be introduced to the network. For the network used in this work, it is required that the weights of the diagonal positions of the synaptic arrays are decreasing from their initial values. Therefore, in the simulated annealed state, an electrical pulse in the opposite direction of the electrical pulse that caused the conductance to increase needs to be applied to some of the ferroelectric synaptic transistors to cause the conductance to decrease. The variation curve of conductance with decreasing voltage pulse (-13 V, 10 ms) is shown in Figure 2.



(1)*Ferrielectric synaptic transistors*

(2)Falling change curve

***Figure 2.** Ferroelectric synaptic transistor.*

3. Simulation of asset pricing solution problem

3.1 Solving Maximum Cutting Problem Simulation

A function minimisation problem is one in which, for a value of x, the function BC, is made to obtain a minimum value in the domain of definition. For this type of problem, the desired functions x_1, x_2 are generally mapped directly to the network energy function. The process of iterative calculation of the network in the direction of the energy function decreases is the process of solving the function minimisation problem by the network. The steady state energy of the network represents the minimum value of the solved function in the domain of definition. The steady-state output of each neuron represents the final value of each input variable.

Mapping the objective function to the network energy function, the correspondence between the network weights and the objective optimisation function is shown in Equation 13 [24,25]:

$$\sum_{j=1}^{n} w_{ij}\, x_j + I_i = -\frac{\partial E}{\partial x_i} \qquad (13)$$

The formula for the pre-calculated weights matrix should be:

$$\alpha \begin{pmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{pmatrix} \qquad (14)$$

where α is the calculated coefficient. The neuron external stimulus size should be：

$$\alpha \begin{pmatrix} I_1 \\ I_2 \end{pmatrix} \qquad (15)$$

In this work, a non-transient chaotic neural network scheme is adopted to iteratively compute x_1, x_2 (neuron output pulse signal normalised to solve the problem.

The final value of the network simulation) with the neural network energy change curve, as shown in Figure 3.

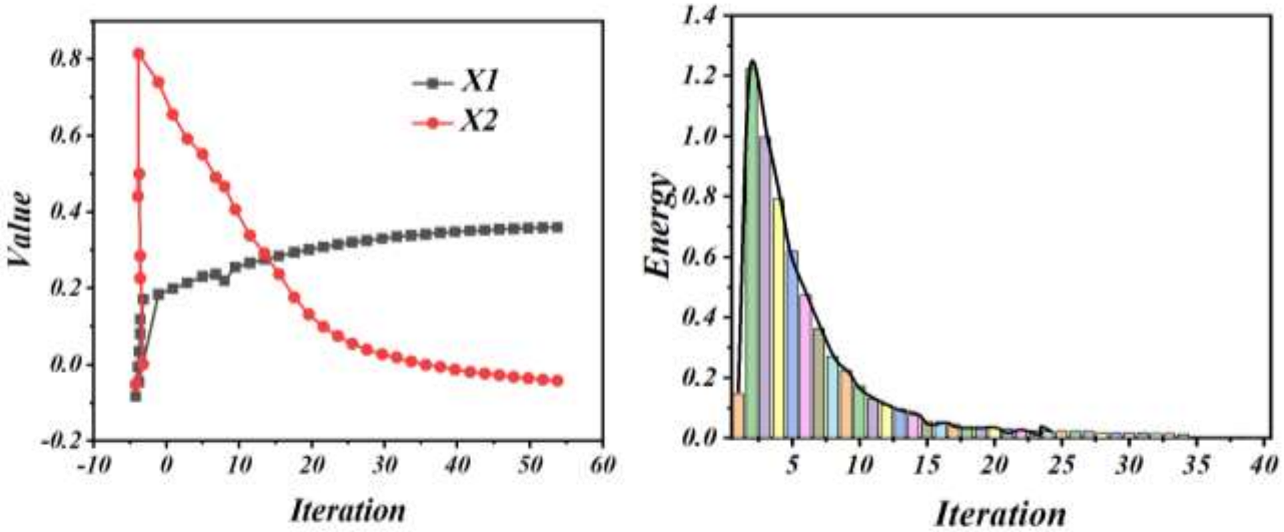


***Figure 3.** (a) Output of two neurons and (b) Schematic of network energy variation with iteration.*

As can be observed from the figure, the neuronal output x_1, x_2, steps up to around 0.8 and 0.2 at the first iteration, respectively, due to the fact that the initial A value is set to (0.5, -0.5) causing the neuron to be rapidly excited by the cumulative value of the endomembrane potential. Subsequently, x_1 decreases and eventually converges around 0.00;x_2 increases and eventually converges around 0.40. The network energy jumps from the initial energy value due to x_1, x_2, and then rapidly decreases and slows down, eventually converging around 0. The final convergence value of the network energy is 0.00001. Solving the original function equation, the minimum value of the original function should be (0, 0.4), and the minimum value is 0. The results of the Hopfield neural network model based on ferroelectric synaptic transistors are basically in accordance with the correct results.

The simulation demonstrates the feasibility of the Hopfield neural network based on ferroelectric synaptic transistor to solve the function minimum problem.

3.2 Solving Maximum Cutting Problem Simulation

The maximum cut problem is a common combinatorial optimisation problem. The maximum cut problem can be described as dividing all endpoints for a given model (which has a certain number of endpoints and some of the endpoints contain connecting lines between them) into two groups such that the maximum number of connecting lines spanning between the two subgroups. For example, for the problem model shown in Figure 2, if a scheme divides nodes 2, 1, 7, and 6 into one group, and nodes 3, 4, and 5 into another group, and cuts the lines between the two groups, the number of lines cut is 4. Therefore, the number of lines cut by this scheme is 4. The purpose of the maximum cut problem is to score the states between the endpoints of the cut lines using Equation 16 [20].

$$\text{Score}_{\,ij} = a_{ij}\left(x_i + x_j - 2x_i x_j\right) \qquad (16)$$

x_i ,$x_j$represent the neuron output values corresponding to the endpoints of the connectivity model, respectively.

The objective function formula is as follows:

$$E = \sum_{i<j} - a_{ij}\left(x_i + x_j - 2x_i x_j\right) \qquad (17)$$

The objective function (Eq. 17) was used as the network energy function. For the connection weights ω_{ij}, between neurons i, j:

$$\omega_{ij} = -\square a_{ij} \qquad (18)$$

where h is the network-wide coefficient of unity. Each neuron fixes the external stimulus to 0.

The neuron damping factor as well as the neuron activation function coefficients are kept at default settings.

Based on Eq. 17 and Eq. 18, keeping the default parameter settings, the pre-designed synaptic weight matrix of the network is calculated, and then the synaptic pre-programming is performed using the network simulation model. Keeping the default settings, a non-transient chaotic strategy is adopted so that the network is computed iteratively from the initial inner membrane potential Y1. The simulation results are shown in Figure 4.

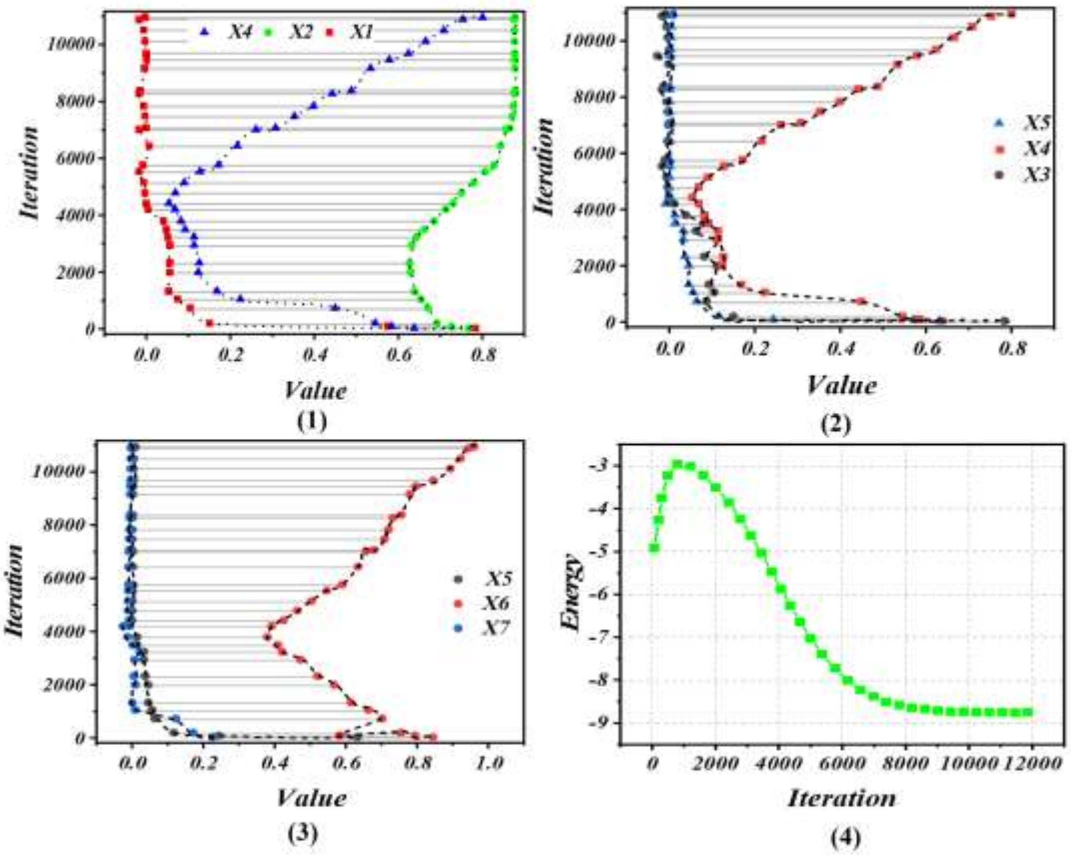


Figure 4. *Simulation results of network based on non-transient chaotic strategy.*

As shown in Figure 4, at the beginning of the network iteration, each neuron is excited to output value due to the preset initial value of the membrane potential within the neuron and leads to a network energy step. Because of the different initial membrane potentials, the initial output values of each neuron are different. After that, the neuron output and network energy start to change iteratively and gradually converge to a fixed value within 12000 iterations.

4. Stock market asset pricing forecasting system

4.1 predictive modelling

This paper mainly introduces how to construct the Hopfield model, and shows the prediction effect of Hopfield model and the comparison with other models. In this paper, we propose to use the Random Forest-based Recursive Feature Elimination (RFE) algorithm for feature selection of basic and technical stock indicators to construct the best feature set, and then use the model combining the Improved Whale Algorithm (GSWOA) and the Hopfield neural network to forecast the Shanghai Stock Exchange Index [26,27].

Based on the feature set of stock price prediction constructed by Random Forest-Recursive Feature Elimination Algorithm, the Hopfield neural network model optimised by Improved Whale Algorithm is established, and the core of the model is the optimisation work, the specific steps are as follows:

1) Processing of the dataset. First, we remove the outliers, fill in the gaps, and classify them according to time. Then, we normalize the dataset. Lastly, we apply recursion to the feature selection.
2) Initialization of the modified whale algorithm. Determine the largest number of iterations t_{max}, the number of whales n, the maximal value u_b and the minimum of the search range in the modified whale algorithm..
3) Initializing the whale's position. Random generation of group whales Xi, 0 (l, e, a), where i is the number of repeated training, e is the learning speed, and a is the number of hidden layer neurons.
4) Calculate the adaptation value corresponding to individual whales. The fitness value is set as the root mean square error (RMSE) of the model validation dataset. If the calculated fitness is the minimum value, it is set as the optimal result for this time and the size is compared with the

global optimal fitness value. If the value is less than the global optimal fitness value, it is replaced.

5) The improved whale algorithm continuously optimises the network parameters by encircling the prey, bubble net attack and searching for the prey until the end of the iteration to get the optimal number of training iterations, learning rate and number of hidden layer neurons.
6) Input the test dataset into the Hopfield model constructed using the optimal parameters and output the predicted values.

4.2 Simulation analysis of experimental result

Selection of indicators

This paper takes the basic stock indicators as the research object, uses the financial a priori knowledge, constructs the indicators so that they can reflect the key information of the stock, which can be classified into two categories of basic indicators and technical indicators in terms of their nature. At the same time, the construction of stock multi-category feature system is also consistent with the trend of deep learning. Therefore, a total of 33 feature indicators are constructed in this paper, 5 basic indicators and 28 technical indicators [28].

1) Opening price: the initial price of the stock on the day.
2) Previous close: the previous day's closing price of the stock.
3) Maximum price: the highest value of the stock price for the day.
4) Lowest price: the lowest value of the day the stock price.
5) up or down: the stock of the day up or down with the previous day's closing price ratio.
6) trend type technical indicators: is under the guidance of the theory of trend analysis, from the stock price and the interrelationship between the indicators, and combined with the characteristics of the averages in order to analyse the stock price trend of strong or weak signs. Trend class line is an effective means to judge the short-term trend of the market and guide investment operations. Trend indicators are the key to the entire system of technical indicators, as they partially make up for the technical indicators can not predict the shortcomings of each wave of the market situation. This paper uses the trend of technical indicators for MA5, MA20, Boll, UB, LB, EMA12, EMA26, DIFF, DEA, MACD, TRIX, ADXR.
7) Oscillating technical indicators: according to the stock volume, price, time and space 4 elements, by a certain formula to find a value, the value of the space around a specific range of rise and fall, and through its rise and fall law to guide the actual work. In this paper, the swing class technical indicators used for KDJ, BIA6, BIA12, RSI6, RSI12, WR6, WR10, MOM, ATR, CCI, ROC.
8) energy-based technical indicators: mainly from the perspective of volume to test the stock price changes, and through the volume of price with the type of indicators to guide the specific operation. This paper uses the energy class technical indicators for VOL, OBV, VR, AD.

Data sources and pre-processing

In order to circumvent the inaccuracy of prediction caused by the randomness of individual stocks or malicious manipulation, which are incidental factors, the target of the study in this chapter is the SSE index which can reflect the rise and fall of the whole stock market. The original stock data selected is the trading data of the SSE index from May 2017 to March 2022, and 85% of the total dataset is used as the training set and the remaining 15% as the test set. The data comes from the stock exchange platform.

There is a very important indicator among the various indicators, i.e. the closing price. According to Dow Theory, the closing price is the most dominant among all prices, and all other prices such as the maximum price represent short-term prices. Within the framework of Dow Theory, the closing price is one of the sources of information available to market participants and a major factor for investors to consider when making investment decisions. In many cases, closing prices are used to represent daily prices. The closing price can simultaneously reflect the day's trading situation and can also be used as a reference for the opening price of the next day. So this paper uses the closing price to make predictions. In the process of modelling neural networks, previous studies have found that the data in the same dataset may have large differences, i.e. the data has a different magnitude, and this can affect the prediction effect of the data. Therefore, in order to eliminate the influence of the volume outline on the prediction results, this paper adopts the Min-Max standardisation to process the data, and the standardisation formula is as follows:

$$X^{m_i} = \frac{X_i - X_{min}}{Xmin_{max}} \qquad (19)$$

Comparative analysis of simulation results

Initiating position of the whale. Group X0 (L, E, a) randomly generated, in which i is the repetition rate, e is the rate of learning, and a is the number of hidden layer neurons. Secondly, the RFE-Hopfield model and Hopfield model are compared and analysed, and the feature set constructed based on the Random Forest-Recursive Feature Elimination algorithm is brought into the Hopfield model with smaller error, which confirms that the prediction performance has been improved after feature selection. Again, comparing the prediction effect of WOA-Hopfield model and Hopfield model, the Hopfield model with improved whale algorithm has better prediction effect, and it can be judged that the improved whale optimisation algorithm can better optimise the parameters of the model. Finally, it can be clearly seen that the RFE-GSWOA-Hopfield model proposed in this paper has the best prediction effect, and the MAPE value, RMSE value and MAE value of this model have reached the minimum value among several models, while the R^2 value has also reached the maximum value among several models. For this reason, the prediction feature set constructed by the Random Forest-Recursive Feature Elimination Algorithm is combined with the Hopfield optimised by the Improved Whale Algorithm to predict the SSE. Neural network model optimised with the improved whale algorithm to predict the SSE index with better prediction accuracy. Table 1 shows model prediction errors. Figures 5 and 6 show the fitting of the first four models with lower overall error indicators, and the curves of the predicted and true values in the figures show that compared with the Hopfield, RFE-Hopfield, and WOA-Hopfield models, the RFE-GSWOA-Hopfield prediction model established in this chapter has a much better fitting effect, and the overall trend of the predicted values matches well with the true values, and at every fluctuation turning point has a good fitting effect, indicating that the error between the two is low.

4.3 Empirical analysis of forecast results

Data selection and processing

CSI 300 index is the first stock index issued by Shanghai and Shenzhen stock exchanges to reflect the trend of the whole market as it selects 300 representative stocks with large scale and good liquidity as its constituents, covering both Shanghai and Shenzhen stock markets. In this paper, the closing price of CSI 300 index is taken as the forecasting object, and the period from 4 January 2011 to 30 December 2022 is chosen as the research interval. The goal of this paper is to forecast the closing price of the index in the short term. Considering that the fundamental data usually remain unchanged in the short term and the influence of the fundamental data of individual stocks on the index is relatively small, a total of 10 characteristics are selected for each trading day: opening price, closing price, high price, low price, turnover, volume, amplitude, up/down, up/down and turnover rate. These features will be used as predictors of the closing price of the index, and the prediction model generates the predicted value of the closing price based on these input features.

Table 1. *Model prediction errors.*

Model	RMSE	MAPE%	MAP	R^2
RNN	43.804	1.084	34.913	0.830
Hopfield	42.301	0.992	32.617	0.831
RFE-Hopfield	39.284	0.873	30.016	0.888
GSWOA-Hopfield	35.617	0.797	27.216	0.918
RFE-GSWOA-Hopfield	29.206	0.594	23.131	0.952

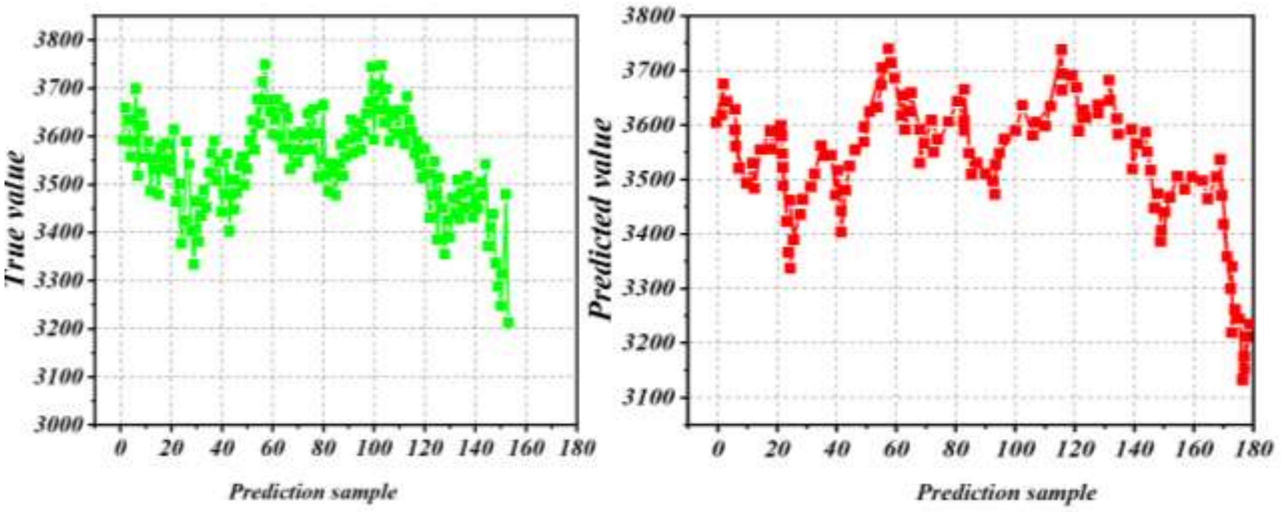


Figure 5. *Simulation results.*

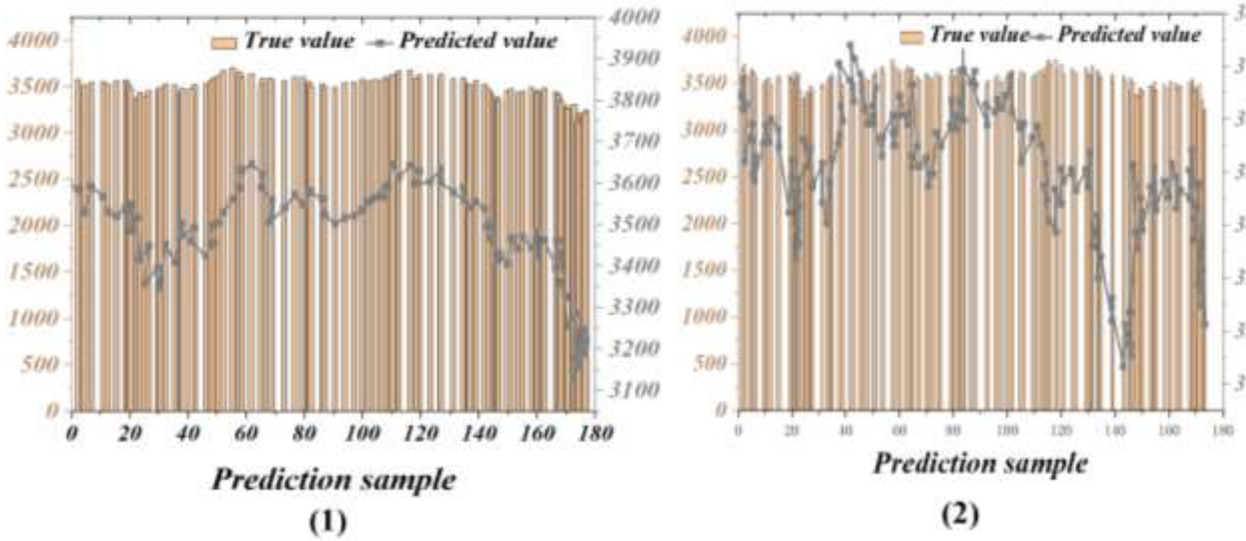


Figure 6. *Simulation results.*

These ten functions shall be collected continuously during the twenty business days of the survey as an initial sample and shall be taken as a marker for the input sample, that is, the target of the forecast model. Based on the time of the tag of the input samples, the samples prior to 1st June 2021 shall be distributed at a random rate of 4: 1 for Nerve Net Model Training, and those from January 1 2021 shall be allocated to a Test Suite for predicting an Index Closing Price. This article takes the sample data from the Choice Financial Terminal database.The Hufffield Model is used to predict the particular value of the closing price of an index, so it is a regression question. The Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Determining Factor (R2) are chosen as the parameters for predicting results：

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \qquad (20)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \qquad (21)$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_i}{y_i}\right| \qquad (22)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\bar{y}_i - y_i)^2} \qquad (23)$$

Comparative analysis

The Hopfield model is better at processing time-series data with temporal dependencies, and is able to better process time-series data and extract feature information more efficiently than the same type of RNN and GRU models, as well as the MLP model which does not have a recurrent structure. To verify this, RNN and GRU models with the same structural parameters as the Hopfield model, as well as an MLP model with 128, 64, and 32 hidden layer neurons, respectively, are built. These four basic models are trained using the same input samples and predictions are made using the test set data. The prediction results of the basic models are shown in Figure 7. In Figure 7, the closing prices predicted by the three models, Hopfield, GRU and RNN, which are capable of handling time series data, are closer to the actual closing prices, while the closing prices predicted by the MLP model deviate from the actual closing prices to the greatest extent and over the longest time interval. For a forecasting model, how well it fits the actual closing price of an index determines its practical value in investment practice: the better the model fit, the more accurate the forecast, the lower the risk of applying the forecast to investment practice, and the more practical value it has. Although the MLP model has been able to maintain the trend of the actual closing price curve of the index over a period of several months, it is clear that the performance of the MLP model is far from satisfactory for the short-term task of predicting the closing price of the index for one trading day in the future. Predictive modelling is used in different works and reported [29,30].

5. Conclusion

Based on Hopfield neural network, This article describes in great detail the complexity of the non-linear and asymmetrical financial system, reveals the potential mechanisms and laws of the stock market, and proposes a prediction method for the stock market, with the following conclusions:

1) This paper mainly introduces Hopfield neural network, respectively, from its network structure, operation mode, convergence principle and other aspects of a detailed introduction to the.

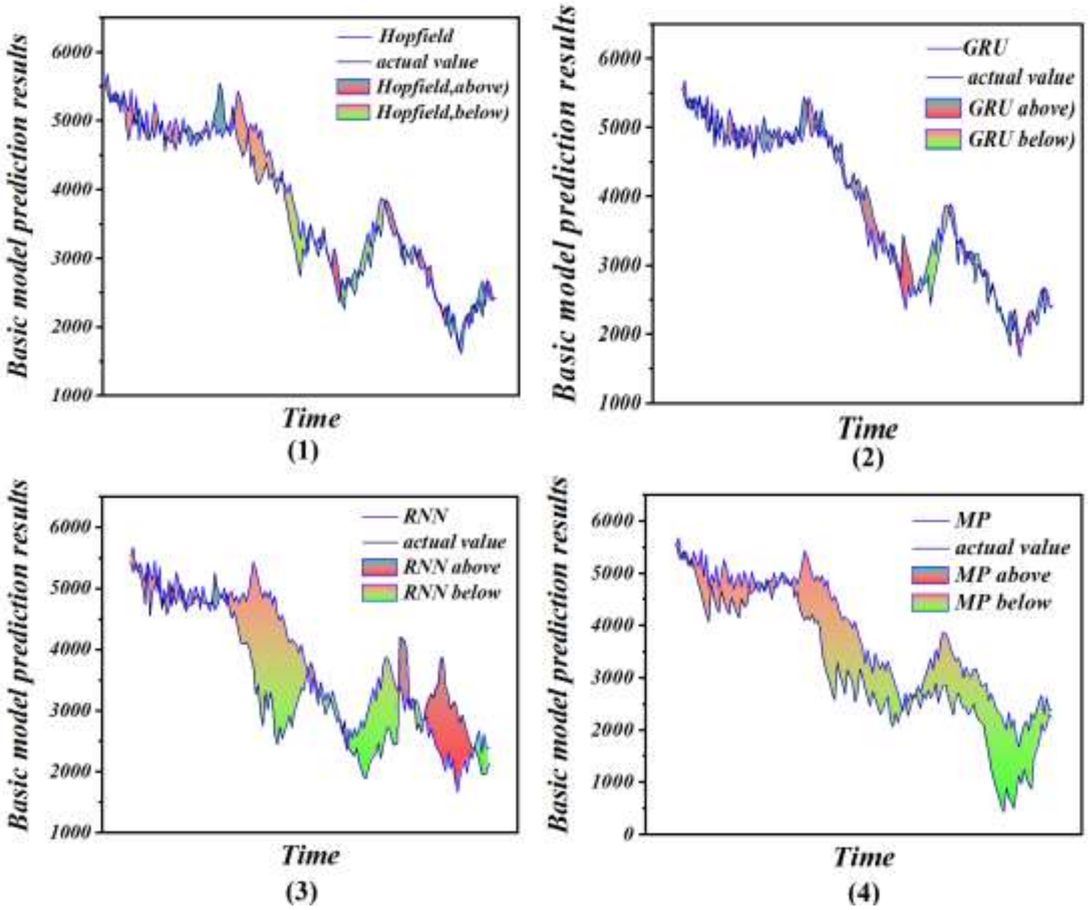


Figure 7. *Comparison of actual and projected results.*

2) Successful simulation implementation of ferroelectric synaptic transistor-based Hopfield neural network based on simulation model for solving function minimisation problem, maximum cut problem, traveller problem.
3) Introducing a stock price prediction model based on RFE-GSWOA-Hopfield. Firstly, the SSE index is selected as the experimental data, and the Recursive Feature Elimination Algorithm is used to select the features of the data to establish a perfect predictive feature set. Secondly, the improved whale algorithm (GSWOA) is used to optimise the important parameters of Hopfield to reduce the influence of human factors and improve the accuracy of model prediction. Finally, the optimised parameters are introduced into the Hopfield network to construct the GSWOA-Hopfield model, and the prediction results of this model are compared and analysed with other models. The experimental results show that: training the Hopfield neural network model with the predicted feature set selected by the recursive feature elimination algorithm improves the prediction accuracy of the model; the improved whale algorithm has obvious advantages in terms of convergence speed and accuracy during the optimisation process; and the MAPE value, RMSE value, and MAE value of this model reach the minimum value among several models, which are 29.206, respectively. 0.594,23.131, and R^2 reaches the maximum value of 0.952 in several models, which proves that the RFE-GSWOA-Hopfield model has better prediction performance and can be effectively used to predict stock data.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of 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
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] Joya, G., Atencia, M. A., & Sandoval, F. (2002). Hopfield neural networks for optimization: study of the different dynamics. *Neurocomputing*. 43(1-4);219-237. https://doi.org/10.1016/s0925-2312(01)00337-x

[2] Junliang Li. (2021). Research on the effectiveness of vulnerability in Chinese stock market based on convolutional neural network [D]. *Henan University of Finance and Politics*. https://doi.org/10.27113/d.cnki.ghncc.2021.000278.

[3] Xing, Weichen. (2020). Simulation of stock market forecasting based on BP neural network [D]. *Guizhou University of Finance and Economics*. https://doi.org/10.27731/d.cnki.ggzcj.2020.000311.

[4] Cong Ruixue,Sun Wei. (2010). A study on radial basis neural network in stock market prediction [J]. *Digital Technology and Application*. (08):104. https://doi.org/10.19695/j.cnki.cn12-1369.2010.08.065.

[5] Ouyang Yulong. (2021). Research on stock market predictability based on financial time series and deep neural network [D]. *Jiangxi University of Finance and Economics*. https://doi.org/10.27175/d.cnki.gjxcu.2021.000769.

[6] Liu N. (2019) Research on the application of deep neural network in China's stock market price prediction [D]. *Hainan University*. https://doi.org/10.27073/d.cnki.ghadu.2019.000890.

[7] Wen, U. P., Lan, K. M., & Shih, H. S. (2009). A review of Hopfield neural networks for solving mathematical programming problems. *European Journal of Operational Research*. 198(3);675-687. https://doi.org/10.1016/j.ejor.2008.11.002

[8] Rebentrost, P., Bromley, T. R., Weedbrook, C., & Lloyd, S. (2018). Quantum Hopfield neural network. Physical Review A. 98(4), 042308. https://doi.org/10.1103/physreva.98.042308

[9] Nasrabadi, N. M., & Li, W. (1991). Object recognition by a Hopfield neural network. *IEEE Transactions on Systems, Man, and Cybernetics*. 21(6);1523-1535. https://doi.org/10.1109/21.135694

[10] Yang, J., Wang, L., Wang, Y., & Guo, T. (2017). A novel memristive Hopfield neural network with application in associative memory. *Neurocomputing*. 227;142-148. https://doi.org/10.1016/j.neucom.2016.07.065

[11] Kobayashi, M. (2013). Hyperbolic Hopfield neural networks. *IEEE transactions on neural networks and learning systems*. 24(2);335-341. https://doi.org/10.1109/tnnls.2012.2230450

[12] Bao, B., Chen, C., Bao, H., Zhang, X., Xu, Q., & Chen, M. (2019). Dynamical effects of neuron activation gradient on Hopfield neural network: numerical analyses and hardware experiments. *International Journal of Bifurcation and Chaos*. 29(04), 1930010. https://doi.org/10.1142/s0218127419300106

[13] Lin, H., Wang, C., Yu, F., Sun, J., Du, S., Deng, Z., & Deng, Q. (2023). A review of chaotic systems based on memristive Hopfield neural networks. *Mathematics*. 11(6), 1369. https://doi.org/10.3390/math11061369

[14] Hu, L., Sun, F., Xu, H., Liu, H., & Zhang, X. (2011). Mutation Hopfield neural network and its applications. *Information Sciences*. 181(1);92-105. https://doi.org/10.1016/j.ins.2010.08.007

[15] Zhang, S., Yu, Y., & Wang, H. (2015). Mittag-Leffler stability of fractional-order Hopfield neural networks. *Nonlinear Analysis: Hybrid Systems*. 16;104-121. https://doi.org/10.1016/j.nahs.2014.10.001

[16] Tatem, A. J., Lewis, H. G., Atkinson, P. M., & Nixon, M. S. (2002). Super-resolution land cover pattern prediction using a Hopfield neural network. *Remote Sensing of Environment*. 79(1);1-14. https://doi.org/10.1016/s0034-4257(01)00229-2

[17] Neshat, M., & Zadeh, A. E. (2010, July). Hopfield neural network and fuzzy Hopfield neural network for diagnosis of liver disorders. In *2010 5th IEEE International Conference Intelligent Systems*. 162-167. https://doi.org/10.1109/is.2010.5548321

[18] Barra, A., Beccaria, M., & Fachechi, A. (2018). A new mechanical approach to handle generalized Hopfield neural networks. *Neural Networks*. 106;205-222. https://doi.org/10.1016/j.neunet.2018.07.010

[19] Wang, S., Schäfer, R., & Guhr, T. (2016). Cross-response in correlated financial markets: individual stocks. *The European Physical Journal B*. 89(105);1-16. https://doi.org/10.2139/ssrn.2892260

[20] Kumbure, M. M., Lohrmann, C., Luukka, P., & Porras, J. (2022). Machine learning techniques and data for stock market forecasting: A literature review. *Expert Systems with Applications*. 197, 116659. https://doi.org/10.1016/j.eswa.2022.116659

[21] Saha, S., Gao, J., & Gerlach, R. (2022). A survey of the application of graph-based approaches in stock market analysis and prediction. *International Journal of Data Science and Analytics*. 14(1);1-15. https://doi.org/10.1007/s41060-021-00306-9

[22] Li, W., Chien, F., Waqas Kamran, H., Aldeehani, T. M., Sadiq, M., Nguyen, V. C., & Taghizadeh-Hesary, F. (2022). The nexus between COVID-19 fear and stock market volatility. *Economic research-Ekonomska istraživanja*. 35(1);1765-1785. https://doi.org/10.1080/1331677x.2021.1914125

[23] Rehman, M. U., Ahmad, N., Shahzad, S. J. H., & Vo, X. V. (2022). Dependence dynamics of stock markets during COVID-19. *Emerging Markets Review*. 51, 100894. https://doi.org/10.1016/j.ememar.2022.100894

[24] Vullam, N., Yakubreddy, K., Vellela, S. S., Sk, K. B., Reddy, V., & Priya, S. S. (2023). Prediction And Analysis Using A Hybrid Model For Stock Market. In *2023 3rd International Conference on Intelligent Technologies (CONIT*). *IEEE*. 1-5 https://doi: 10.1109/CONIT59222.2023.10205638.

[25] Umar, M., Farid, S., & Naeem, M. A. (2022). Time-frequency connectedness among clean-energy stocks and fossil fuel markets: Comparison between financial, oil and pandemic crisis. *Energy*. 240, 122702. https://doi.org/10.1016/j.energy.2021.122702

[26] Yousaf, I., Patel, R., & Yarovaya, L. (2022). The reaction of G20+ stock markets to the Russia–Ukraine conflict "black-swan" event: Evidence from event study approach. *Journal of Behavioral and Experimental Finance*. 35, 100723. https://doi.org/10.1016/j.jbef.2022.100723

[27] Benlagha, N., Karim, S., Naeem, M. A., Lucey, B. M., & Vigne, S. A. (2022). Risk connectedness between energy and stock markets: Evidence from oil importing and exporting countries. *Energy Economics*. 115, 106348. https://doi.org/10.1016/j.eneco.2022.106348

[28] Wong, J. B., & Zhang, Q. (2022). Stock market reactions to adverse ESG disclosure via media channels. *The British Accounting Review*. 54(1), 101045. https://doi.org/10.1016/j.bar.2021.101045

[29]Akram M. Musa, Abu-Shaikha, M., & Al-Abed, R. Y. (2025). Enhancing Predictive Accuracy of Renewable Energy Systems and Sustainable Architectural Design Using PSO Algorithm. *International Journal of Computational and Experimental Science and Engineering,* 11(1). https://doi.org/10.22399/ijcesen.842

[30]Abu-Shaikha, M., & Nasereddin, S. (2025). Predicting Media Impact: A Machine Learning Framework for Optimizing Corporate Communication Strategies in Architectural Practices. *International Journal of Computational and Experimental Science and Engineering,* 11(1). https://doi.org/10.22399/ijcesen.1032