Received 19 November 2023, accepted 13 January 2024, date of publication 18 January 2024, date of current version 29 January 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3355446

APPLIED RESEARCH

AI-Driven Intraday Trading: Applying Machine Learning and Market Activity for Enhanced Decision Support in Financial Markets

MIN-CHIH HUNG[1], AN-PIN CHEN[2], AND WAN-TING YU[1]
[1]Institute of Information Management, National Yang Ming Chiao Tung University, Hsinchu 300093, Taiwan
[2]Department of Finance, Asia University, Taichung 413305, Taiwan

Corresponding author: Min-Chih Hung (dana6405@gmail.com)

ABSTRACT In response to the unpredictable fluctuations in the global economic landscape, and with the aim of mitigating overnight risks, the stock market has seen a substantial increase in the number of day traders. However, day traders often fall prey to emotional influences, resulting in abrupt and irrational shifts in market prices. Consequently, when supporting investors engaged in day trading, it becomes imperative to furnish them with decision-making assistance to reduce trading risks. To address this challenge, the present study leverages a neural network architecture paired with a daily market activity structure. This combination allows us to delve into the dynamic behaviors governing day trading in Taiwan's weighted index futures. By uncovering the underlying knowledge rules of the futures market, we can establish a model for predicting day-trading directions and employ effective trading strategies. The outcomes of this research indicate that the accuracy attained through this research methodology surpasses that of the random walk theory used by the control group. The discernible divergence in results confirms that lower-risk entry points within the intraday market can be identified through this approach. Recognizing these low-risk entry points holds the potential to aid investors in managing market risks and enhancing their opportunities for profit.

INDEX TERMS Artificial intelligence (AI), day trading, market logic, physical-force behavior, trading strategy.

I. INTRODUCTION

Owing to uncertainties caused by the COVID-19 pandemic in early 2020, major global stock markets have collapsed or dropped sharply. The Dow Jones Industrial Average experienced its largest quarterly decline since 1987. However, after governments intervened, global markets began to recover [1]. The early 2022 Russo-Ukrainian War heightened geopolitical risks in global stock markets, particularly in the increasingly interconnected world of global financial markets [2]. As the global economic system is closely interconnected, Taiwan was not immune to this upheaval. Taiwan is a thin market, which is vulnerable to the impact of news, resulting in severe stock market volatility and overnight risk [3]. To avoid this risk, investors have adopted intraday trading, also known as "day trading," which is a method of offsetting trades on the same day to close all positions within one trading day. Although intraday investment operations can avoid losses caused by overnight risk, the increase in the number of intraday trading participants has led to a substantial increase in shares traded. As per statistics from the Taiwan Stock Exchange, the total number of shares traded on the day is offset; it accounts for an increase of 28.43% of the market, from 0.36% when it opened on January 6, 2014, to 26.67% on the day of July 18, 2023. Intraday markets are often affected by the emotions of the participants, causing irrational stock prices. The momentary changes in profitability increase while simultaneously increasing risks.

Scholar Fama [4] proposed the Random Walk Hypothesis, which posits that short-term fluctuations in stock prices are

The associate editor coordinating the review of this manuscript and approving it for publication was Vijay Mago.

random, meaning they do not follow any distinct trends or patterns. According to this hypothesis, stock prices at any given point in time are not influenced by previous price movements, making it difficult to accurately predict the direction of stock prices in the short term. This theory challenges the effectiveness of short-term market timing and technical analysis, emphasizing the importance of long-term investment and diversification. While the Random Walk Hypothesis highlights the randomness of short-term price fluctuations, it also acknowledges the possibility of long-term trends influenced by a company's fundamentals and macroeconomic factors.

In contrast, Steidlmayer [5] presented the market logic theory, contending that market development is not random [6]. Market prices, he argued, are shaped by participants with varying timeframes who engage in passive or active bidding, thus influencing market price movements. Steidlmayer's theory is grounded in the idea that participants with different timeframes hold varying perspectives on the same stock. Consequently, the market cannot simultaneously cater to the needs of all participants, and no single price can represent a fair value.

Through the lens of the market logic theory, the intraday market is viewed as a fair price range, often referred to as the "value area." Within the defined value area, which constitutes the market's predominant residence, traders have the opportunity to capitalize on potential profits. By strategically purchasing in regions below the established value and selling in areas above it, traders can adeptly pinpoint intraday entry points with comparatively lower risk. The choice of the entry point is a pivotal aspect of a trader's strategy as it determines the price at which a security will be bought or sold. Recognizing low-risk entry points has the potential to increase the likelihood of traders achieving stable returns. Moreover, Steidlmayer observed that market price fluctuations are influenced by irrational investor behavior, highlighting the non-linear relationship between risk and reward in the market.

In the face of nonlinear challenge, artificial intelligence methodologies prove effective in deciphering the rules within an uncertain environment. Among the most prevalent methods for predicting these rules is the utilization of neural networks. Neural networks construct their understanding of the problem by means of self-learning, forming a nonlinear predictive model through iterative learning from historical data. Therefore, this study employs neural networks to gain insights into the dynamic behavior of market value changes. It does so by inputting the market's logical structure and, ultimately, generating predictions for market direction. This serves as a valuable auxiliary tool for intraday traders as it mitigates the intraday market risk faced by investors.

II. RELATED WORK

Market Logic, as elucidated by Fama [4], serves as a logical framework for comprehending market value through statistical background analysis and the representation of the worth of financial assets. This conceptual framework functions as a decision support tool, aiding in the organization and visualization of market activities for the purpose of scrutinizing fluctuations in market prices. Originally presented in 1984, this theory offers valuable insights into the realm of financial markets.

A. MARKET LOGIC

Market Logic, also known as Market Profile, is a set of tools for observing changes in market value. It is used to compose a Time, Price, and Opportunities (TPO) chart (Fig. 1) and is based on the normal distribution curve. The basic units in the TPO chart are indicated by the relative letters associated with the TPOs, such as A to J in Fig. 1. Each letter represents the range of high and low prices within half an hour. The value area, i.e., the area where the most transactions (approximately 70%) occur within the time period, is indicated by the blue letters in the figure. In Fig. 1, the value area ranges from 5718 to 5728, i.e., the price range that buyers and sellers considered the fairest. Market participants in the TPO chart can be divided into intraday traders and other-timeframe traders. The other-timeframe traders only enter the market when the value of the market is higher or lower than the price, and they can influence the value of the market.

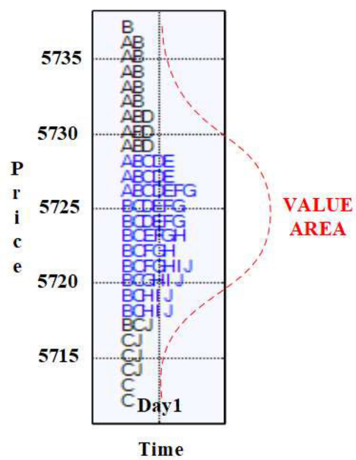

FIGURE 1. TPO chart representing the relative letters of time, price, and opportunity.

From the intraday TPO chart, we can obtain various information generated by the market. Some important terms are defined below.

Initial balance: The buyer and seller react to the price range based on various news before the opening. In Fig. 1, for periods A and B, the initial balance range is from 5717 to 5737.

Range Extension: The range of price activity above or below the initial balance.

Point of control: The price of the longest TPOs, as shown in Fig. 1 at 5726.

Tail: The price activity within the range of a single TPO but above or below the value area, as shown in Fig. 1, where the buying tail range is from 5712 to 5713.

Extension: The price range for the last period, J. It ranges from 5714 to 5721.

As the market is continuously developing, we can observe more than intraday market activities in the TPO chart.

Therefore, we incorporate the TPO chart from the preceding day into the analysis of the present day. The TPO charts of consecutive days (as shown in Fig. 2) are relative at the beginning of Day 2, as buying activity can be divided into initial buying and responsive buying (just as selling activity is divided into initial selling and responsive selling).

Initial buying of Day 2: The buyer's position in this range is above the value area of Day 1, which is the buyer's active attack buying power. The initial buying range is from 5716 to 5736.

Responsive buying: The buyer's position in this range is above the value area of Day 1. This is the buyer's response to the buying power arising from the price being lower than on Day 1. The responsive buying range is from 5700 to 5715.

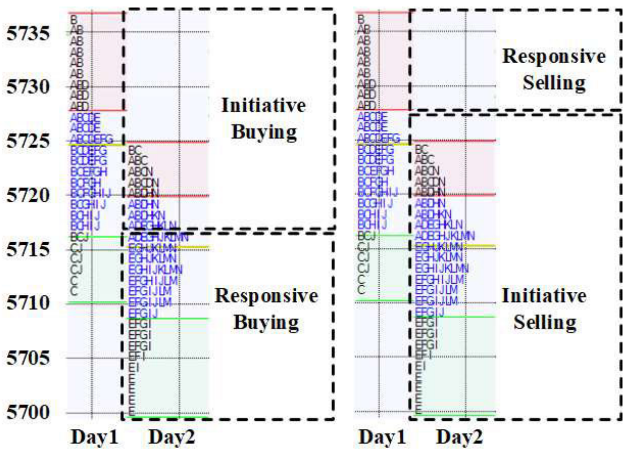

FIGURE 2. Market activity chart.

Firich [7] analyzed the market based on the initial balance of the US stock market. The point where the price breaks the initial balance is a good trading opportunity. If the trader can observe the market direction, it will be an opportunity to place an order with a high probability of success. In the work by Chen et al. [8], market profile theory and technical analysis are employed to develop a neural network model, thereby improving predictive accuracy and profitability in the TAIEX futures market. Findings reveal superior short-term performance for qualitative market profile indicators, whereas quantitative indicators demonstrate enhanced long-term trend prediction capabilities. Wu et al. [9] analyzed the market based on the double distribution trend day of Taiwan Capitalization Weighted Stock Index (TAIEX) futures. The results show that the accuracy was 57.45% and the returns were 24.09 points. Huang et al. [10] used the point of control of TAIEX futures. Leveraging displacements across various trading days for the identification of extremely short-term entry and exit points, with the historical Point of Control (POC) serving as a valuable benchmark for entry points. In light of the aforementioned, it is evident that market logic offers distinct advantages to traders engaged in market activities.

The methods mentioned earlier are confined to the TPO Chart of a single trading day. However, our approach goes beyond this limitation by incorporating the TPO Chart of the previous day into the Activity Chart. This enhancement is based on a more comprehensive understanding of the market's continuity, recognizing that the market operates continuously and is influenced by the events of the previous day.

In traditional TPO Charts, a buying action is treated as a singular event. In contrast, within our Activity Chart, buying actions are subdivided into two scenarios: active buying and passive buying. Active buying signifies proactive participation in the market, while passive buying may be influenced by factors such as the trend from the previous day or other market conditions, prompting traders to passively engage in buying.

By considering the continuity of market activity, our approach provides a more comprehensive and dynamic analysis of the market. This enhanced understanding of market continuity contributes to more accurate predictions and interpretations of market changes, allowing traders to adapt more flexibly to different market scenarios. Therefore, our approach holds an advantage in capturing market complexity and variability, offering valuable insights for trading decisions.

B. RESILIENT PROPAGATION

Resilient propagation (Rprop) stands as a supervised learning heuristic tailored for feedforward artificial neural networks, originating from the collaborative efforts of Riedmiller and Braun in 1992 [11]. Its application has permeated diverse domains, finding widespread use across a spectrum of fields [12], [13], [14].

Shastri et al. [15] introduced an approach involving the initial computation of sentiment scores using a naïve Bayes classifier, followed by the application of neural networks to these scores and historical stock datasets. Models incorporating input from sentiment analysis and historical data within neural networks demonstrate the capacity to forecast prices. Experimental findings revealed that, in optimal scenarios, the accuracy surpassed the 90% threshold. Jothimani and Yadav [16] proposed neural networks and support vector regression to predict stock prices. From 2008 to 2015, the components of the Nifty index were tested for eight years of model performance. Compared with the traditional "buy and hold" strategy, this model has a higher return on investment. Mitilineos and Artikis [17] proposed a set of neural networks, using a genetic algorithm as a neural network training and optimization tool to predict future stock market index values, proving their superiority over standard benchmark technologies. In summary, the study of artificial (computational) intelligence methods proves that their results provide strong support for technical strategies.

III. METHODS

The experimental flowchart of this study is shown in Figure 3, and the detailed description is as follows. The data source used for this research model was the historical data of TAIEX futures. Data were preprocessed to convert the daily historical data into a one-minute segment chart (Fig. 4). Next, this segmented chart was converted into a one-minute market activity chart (Fig. 5), and the dataset was cut with a moving window to generate the n-minute (n = 5, 15, 30, and 45) feature values needed.

Next, the features were input into a resilient-propagation neural network for learning. After the learning was completed, the market output signals were attempted after 5, 15, 30, and 45 minutes, inputting the buying and selling signals into the experimental groups, and simultaneously, random buying and selling trades were generated. The signal was sent to the random module, trading was conducted as per the trading strategy, and the performance was evaluated.

During data preprocessing, we calculated the input and output values. The calculation of the input parameters was divided into three steps:

1. Market activity structure calculation,
2. Dynamic physical behavior calculation, and
3. Data normalization.

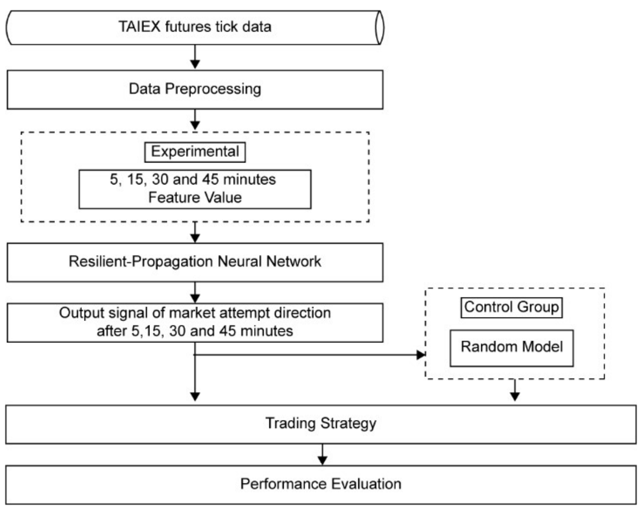

FIGURE 3. Experimental flowchart.

A. DATA PREPROCESSING

Initially, the TAIEX futures tick dataset, employing a unit of N minutes, was employed to determine the price's high and low-point range, resulting in the creation of a bar chart. Subsequently, the TPO letters were populated based on the high and low range of the bar, shaping a segmented chart structure, as depicted in Fig. 4. Then, over time, the TPOs of the segmented chart were drawn to the corresponding price column, and the market activity chart was generated, as shown in Fig. 5.

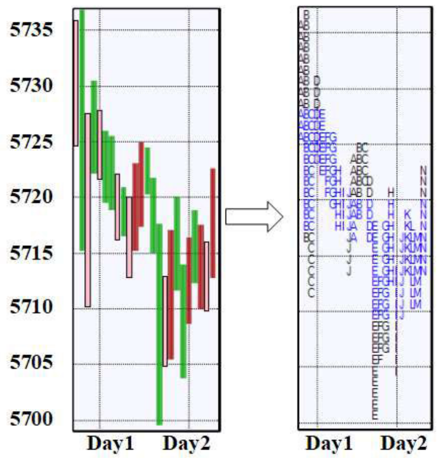

FIGURE 4. TAIEX data converted to a segmented chart structure.

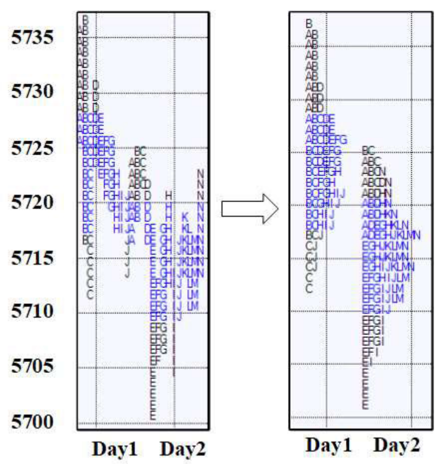

FIGURE 5. Conversion of segmented into market activity chart structure.

Derived from the market activity chart, we applied 15 distinct market activity structures, subsequently producing 45 input feature values, outlined in Table 1:

B. DYNAMIC PHYSICAL BEHAVIOR AND DATA NORMALIZATION

According to Chen and Hsu [18], adding dynamic physical behavior changes can help analyze the difference between causality in financial dynamics and increase the neural network learning reliability. The correlation observed between preceding and subsequent data points in a time series implies a cause-and-effect relationship, signifying a significant interdependence within the dataset. This interconnectedness showcases how past events impact future occurrences, contributing to the overall dynamics and patterns within the time series data. Therefore, the input variables in this experiment were calculated as dynamic physical behavior changes to represent the input variables in the intensity and the direction of the energy change during the calculation. For a given minute t and market activity structure raw value rv(t), the

TABLE 1. Features values extracted using the market activity structure.

No	Market Activity	Structure	Features Value
1	Responsive Selling	Tail	1. rv(t), 2.fp(t), 3.sp(t)
2	Responsive Selling	Range Extension	4. rv(t), 5.fp(t), 6.sp(t)
3	Responsive Selling	Extension	7. rv(t), 8.fp(t), 9.sp(t)
4	Initiative Selling	Tail	10. rv(t), 11.fp(t), 12.sp(t)
5	Initiative Selling	Range Extension	13. rv(t), 14.fp(t), 15.sp(t)
6	Initiative Selling	Extension	16. rv(t), 17.fp(t), 18.sp(t)
7	Initiative Selling	POC	19. rv(t), 20.fp(t), 21.sp(t)
8	Initiative Buying	POC	22. rv(t), 23.fp(t), 24.sp(t)
9	Initiative Buying	Extension	25. rv(t), 26.fp(t), 27.sp(t)
10	Initiative Buying	Range Extension	28. rv(t), 29.fp(t), 30.sp(t)
11	Initiative Buying	Tail	31. rv(t), 32.fp(t), 33.sp(t)
12	Responsive Buying	Extension	34. rv(t), 35.fp(t), 36.sp(t)
13	Responsive Buying	Range Extension	37. rv(t), 38.fp(t), 39.sp(t)
14	Responsive Buying	Tail	40. rv(t), 41.fp(t), 42.sp(t)
15	None	Rotation factor	43. rv(t), 44.fp(t), 45.sp(t)

first-order physical change at minute t is defined as:

$$fp\,(t) = \frac{rv\,(t) - \mathrm{rv}\,(t-1)}{rv\,(t-1)} \tag{1}$$

For a given minute t and the first-order physical change $fp\,(t)$, the second-order physical change on minute t is defined as:

$$sp\,(t) = fp\,(t) - fp\,(t-1) \tag{2}$$

An example of dynamic physical behavior calculation is as follows. We have four records of Responsive Selling Tail, as presented in table 2. When t is 2023/09/12 9:02, rt(t) is 29 and rt(t−1) is 25, so fp(t) = (29−25)/25 = 0.16, and sp(t)=0.16−(−0.107142857) = 0.267142857.

TABLE 2. Calculation results of dynamic physical behavior.

Datetime	T	rv(t)	fp(t)	sp(t)
2023/09/12 9:00	t−2	28	Null	null
2023/09/12 9:01	t−1	25	−0.107142857	null
2023/09/12 9:02	t	29	0.16	0.267142857
2023/09/12 9:03	t+1	21	−0.275862069	−0.435862069

Neural networks learn a variety of data. To eliminate any difference in units or a large gap in the data, we normalized the input data to strengthen the learning effect. Initially, the data underwent scaling to the [0, 1] interval using the Min-Max Normalization method, employing the following formula:

$$X_{new} = \frac{X - X_{min}}{X_{max} - X_{min}} \in [0, 1]\,, \tag{3}$$

where X_{max} and X_{min} represent the maximum and minimum values in the dataset, respectively. Then the data were sorted by size and evenly distributed over the interval [0, 1]. After processing 15 market activity structures through the above process, we can get 45 input feature values.

Next, the relatively high and low closing prices (RHLC) were calculated for the highest, lowest, and closing prices within n minutes (n = 5, 15, 30, 45) in the future. Through the calculation of RHLC, we can understand the price changes of buyers and sellers in the next n minutes (n = 5, 15, 30, 45). If the buyer power is higher than the seller power, the market in the next n minutes will trend upward. For a given n-minute range of rt and price P, the RHLC on rt is defined as:

$$\begin{aligned} RHLC\,(rt) &= (max\,(P_h\,(rt)) - P_c\,(rt)) \\ &\quad - (P_c\,(rt) - min\,(P_l\,(rt)))\,, \end{aligned} \tag{4}$$

where $P_h\,(rt)$, $P_c\,(rt)$, and $P_l\,(rt)$ represent the n-minute price high, close, and low.

To allow the neural network to focus on learning the trend direction, we grouped the RHLC again as follows:

$$GRHLC\,(rt) = \begin{cases} 1, & RHLC\,(rt) > 0 \\ 0.5, & RHLC\,(rt) = 0 \\ 0, & RHLC\,(rt) < 0 \end{cases} \tag{5}$$

The model in this study used the C# programming language for coding, and the resilient-propagation neural network used Encog's library [19] with an input feature value of 45 and a predicted output value of 1. Zhang et al. [20] highlighted the reliability of accuracy in a neural network with a single hidden layer. In accordance with these findings, we configured the neural network with one hidden layer. Davies [21] proposed to find the most suitable node number setting through trial-and-error method. After considerable trial and error, 22 hidden layer nodes, 300 epochs, and the sigmoid activation function were set as the neural network parameters. The resultant output from the trained neural network fell within the range of 0 to 1. This study used the threshold mechanism to strengthen the accuracy of the prediction. The predicted output value was higher than 0.70 as a long signal, and the predicted output value was less than 0.25 as a short signal.

After completing the neural network learning, we used trading strategies to simulate market operations and produce the final profit and loss analysis report to evaluate the effectiveness of the neural network learning.

The trading strategy of this research is explained as follows:

1. The maximum number of positions held is one, and the transaction cost is two points.
2. Long signal output: short positions are covered, and index futures are bought at the opening price in the next minute.
3. Short signal output: long positions are covered, and index futures are sold at the opening price in the next minute.
4. Hold and close position: When the position holding time is reached, the position is closed at the opening price in the next minute.
5. Closing the position at closing time: If the position is still held at 13:30, the position is closed at 13:30.

Finally, this study used two evaluation methods as models. The evaluation methods used to compare the performance of good and bad indicators and measure the model's simulated trading performance are described as follows.

Accuracy is computed by dividing the number of profitable transactions, where the transaction profit (after closing the position and deducting two points) exceeds zero, by the total number of transactions conducted throughout the simulated trading period. The calculation formula is as follows:

$$\text{Accuracy} = \frac{\textit{Number of Profitable Transactions}}{\textit{Total Number of Transactions}} \tag{6}$$

The computation of profitability involves dividing the cumulative profit amassed throughout the simulated trading period by the total number of transactions conducted within that specific trading timeframe. The calculation formula is as follows:

$$\text{Average Profit} = \frac{\textit{Total Profit}}{\textit{Total Number of Transactions}} \tag{7}$$

This formula provides a quantitative measure, offering insights into the financial performance of a trading strategy by assessing the average profit generated per transaction over the specified trading period. It serves as a valuable metric for evaluating the effectiveness and success of the trading approach deployed during the simulation.

IV. EXPERIMENTS

In the research conducted, the model was structured with four experimental groups alongside a control group. Following Kearns' recommendation [22], a strategic allocation of approximately 20% to 30% of the dataset was adopted for testing purposes, aiming to achieve optimal performance. This approach aligns with best practices in experimental design, ensuring a robust evaluation of the model's efficacy by dedicating a significant portion of the dataset to testing. Consequently, the data source was partitioned into 80% for training and 20% for testing to facilitate robust model evaluation. The dataset utilized in this study covered the time span from October 3, 2022, to September 28, 2023, encompassing a total of 71,823 one-minute data points. To facilitate model training and evaluation, the dataset was split into training and testing sets. The training dataset, spanning from October 3, 2022, to July 21, 2023, comprised 57,452 data points, while the testing dataset, covering the period from July 24, 2023, to September 28, 2023, included 14,371 data points (as shown in Fig. 6). It is noteworthy that the training and testing times were consistent across both the experimental and control groups. Based on the experimental group's neural network trading signals and trading strategies, positions were bought; held for 5, 15, 30 and 45 minutes (with four instances of holding for each duration); and then closed. Subsequently, the total profit or loss was calculated. Each profit or loss included handling fees and transaction taxes.

To establish that fluctuations in market prices are influenced by the diverse trading behaviors of market participants, this study seeks to challenge the notion of a random walk in the market. Instead, it posits that the market exhibits discernible behavioral patterns and rules that can be interpreted. Hence, this investigation employs a control group-random transaction model for comparison with the proposed neural network model. This approach aims to assess and contrast the respective strengths and weaknesses in terms of accuracy between the two models. The trading strategy of the random trading model is to make random judgments for long or short futures based on the time point when the trading signal appears in the neural network model. Taking a buy and hold for 5 minutes as an example, the model will randomly enter the market based on the neural network of the experimental group for buying and selling signals while entering the market. When the random value generated by the control group is higher than 0.5, it will be used to trade long positions. If the random value is less than 0.5, the Taiwan index futures must be shorted. Should the randomly generated value equate to 0.5, it will undergo regeneration. At the same time, the trading strategy and trading unit settings of the random trading model are the same as those in the experimental group, considering handling fees and transaction taxes.

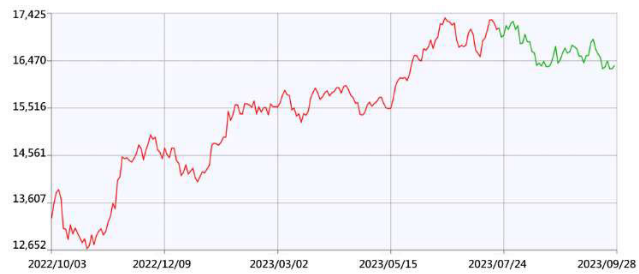

FIGURE 6. Trend chart during the experimental period.

To evaluate how the feature values extracted from the market activity chart, spanning different timeframes in this experiment, influence the accuracy of predicting various time intervals, we organize the experimental data into four categories designated as A, B, C, and D. To obtain a more unbiased comprehension of the model's execution outcomes, each model from both the experimental and control groups will undergo an independent rerun 30 times. Simultaneously, to enhance the objectivity in understanding the model's execution outcomes, each model from both the experimental and control groups will be re-executed 30 times. The subsequent description presents the statistical results post 30 executions.

Experimental group A consisted of 5 one-minute periods of market activity structure, which was used as the input variable of the neural network. The experimental results are summarized in Table 3.

TABLE 3. Experimental group A results.

Holding Periods	Accuracy	Total Profit	Transactions	Average Profit
5 minutes	0.526072330	540	2,378	0.227082
15 minutes	0.716483516	8,356	910	9.182418
30 minutes	0.671823722	26,427	2,133	12.389590
45 minutes	0.672734468	40,606	2,527	16.068860

The results delineate the substantial influence of holding time on model accuracy. Remarkably, the peak accuracy of 71.64% is achieved at the 15-minute holding interval, closely trailed by the 45-minute duration. This underscores the critical consideration of holding periods in optimizing the model's precision, with the 15-minute timeframe standing out as particularly noteworthy.

Experimental group B comprised 15 one-minute intervals of market activity structure, serving as the input variable for the neural network. The outcomes of the experiments are succinctly presented in Table 4:

TABLE 4. Experimental group B results.

Holding Periods	Accuracy	Total Profit	Transactions	Average Profit
5 minutes	0.523187908	2,544	2,544	0.873926
15 minutes	0.731663685	18,299	1,677	10.911750
30 minutes	0.672222222	30,805	2,340	13.164530
45 minutes	0.705392810	50,198	3,004	16.710390

Table 4 provides a comprehensive overview of the performance of experimental group B across different holding periods. The standout result is the impressive accuracy of 73.17% observed during the 15-minute holding duration.

Experimental group C consisted of 30 one-minute periods of market activity structure, which was used as the input variable of the neural network. The experimental results are summarized in Table 5:

TABLE 5. Experimental group C results.

Holding Periods	Accuracy	Total Profit	Transactions	Average Profit
5 minutes	0.520529071	5,046	3,629	1.390466
15 minutes	0.643268124	18,224	2,607	6.990410
30 minutes	0.631189264	40,318	4,322	9.328552
45 minutes	0.659565024	62,780	4,506	13.932530

Experimental group C exhibited the highest accuracy when holding for 45 minutes, closely followed by the 15-minute duration. However, the accuracy for predicting market fluctuations within the initial 5-minute period was comparatively lower at 52.05%. This emphasizes the varying predictive strengths of the model across different holding times, with 45 minutes emerging as the most accurate.

Experimental group D consisted of 45 one-minute periods of market activity structure, which was used as the input variable of the neural network. The experimental results are summarized in Table 6:

TABLE 6. Experimental group D results.

Holding Periods	Accuracy	Total Profit	Transactions	Average Profit
5 minutes	0.536866359	2,676	3,038	0.880843
15 minutes	0.595289079	19,654	2,802	7.014276
30 minutes	0.626232742	39,150	4,056	9.652367
45 minutes	0.644553073	49,876	4,296	11.609870

Experimental group D exhibited its highest accuracy when holding for 45 minutes, reaching 64.45%. However, the accuracy for the 5-minute holding duration was below 53.68%. These results highlight the varying performance of the model across different holding times, with 45 minutes demonstrating the most favorable accuracy.

Comparing the accuracy of the above four groups of experiments, we can find that the 15 one-minute periods of market activity structure, and 15 minutes buy and hold have better results (as shown in Fig. 7). Using this setting, under the same experimental conditions, we use the historical data of TAIEX Futures in the past 5 years for experiments (as shown in Fig. 8). The data set settings are presented in Table 7.

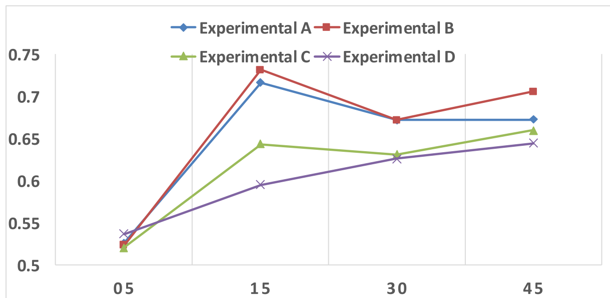

FIGURE 7. Accuracy analysis chart.

TABLE 7. Dataset settings from 2018 to 2022.

	Training Dataset			Testing Dataset		
Year	Start Date	End Date	Record	Start Date	End Date	Record
2018	2017/10/02	2018/07/23	58,649	2018/07/24	2018/10/01	14,670
2019	2018/10/01	2019/07/19	58,352	2019/07/22	2019/10/01	14,668
2020	2019/10/01	2020/07/22	58,651	2020/07/23	2020/09/30	14,970
2021	2020/10/05	2021/07/22	58,352	2021/07/23	2021/10/01	14,671
2022	2021/10/01	2022/07/21	58,652	2022/07/22	2022/09/30	14,970

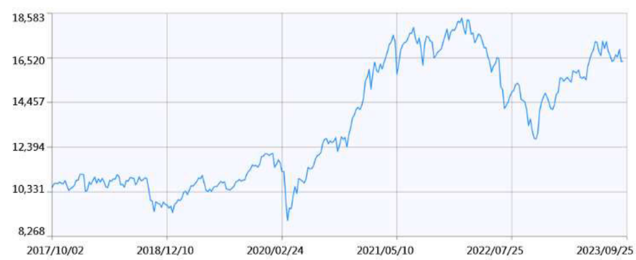

FIGURE 8. Line chart of weekly closing prices over the past 5 years.

TABLE 8. Results of experiments in the past five years.

Year	Accuracy	Total Profit	Transactions	Average Profit
2018	0.694958848	11,432	1,944	5.880658436
2019	0.664340102	8,531	1,576	5.413071066
2020	0.638725490	24,291	2,040	11.907352940
2021	0.633333333	14,396	1,680	8.569047619
2022	0.675261324	12,686	1,435	8.840418118

TABLE 9. Results of the F-test for homogeneity of variances between the experimental and control.

Holding Periods	Experimental	Accuracy	Control	Accuracy	F	P	Test results
5 Minutes	5 one-minute	0.526072330	Random	0.455004205	1.099246238	0.400307372	Reject H_0
	15 one-minute	0.716483516	Random	0.465934066	3.549538644	0.000521301	Do not reject H_0
	30 one-minute	0.671823722	Random	0.481481481	2.301697976	0.014094277	Do not reject H_0
	45 one-minute	0.672734468	Random	0.464582509	1.575106210	0.113582770	Reject H_0
15 Minutes	5 one-minute	0.523187908	Random	0.423565785	2.576422634	0.006534523	Do not reject H_0
	15 one-minute	0.731663685	Random	0.479427549	1.580663353	0.111806800	Reject H_0
	30 one-minute	0.672222222	Random	0.479059829	2.060815132	0.028063410	Reject H_0
	45 one-minute	0.705392810	Random	0.469374168	1.716133253	0.075904841	Reject H_0
30 Minutes	5 one-minute	0.520529071	Random	0.428492698	1.101315906	0.398369343	Reject H_0
	15 one-minute	0.643268124	Random	0.450326045	1.802644683	0.059151427	Reject H_0
	30 one-minute	0.631189264	Random	0.439379917	2.065539084	0.027684299	Reject H_0
	45 one-minute	0.659565024	Random	0.489125610	1.876432145	0.047792223	Reject H_0
45 Minutes	5 one-minute	0.536866359	Random	0.426267281	1.753677998	0.068127367	Reject H_0
	15 one-minute	0.595289079	Random	0.443254818	1.082512065	0.416201734	Reject H_0
	30 one-minute	0.626232742	Random	0.463017751	1.197564273	0.315273741	Reject H_0
	45 one-minute	0.644553073	Random	0.478351955	1.666200745	0.087603812	Reject H_0

TABLE 10. Results of the student's T-test for accuracy between the experimental and control.

Holding Periods	Experimental	Accuracy	Control	Accuracy	t stat	P	Test results
5 Minutes	5 one-minute	0.526072330	Random	0.455004205	4.997575052	5.66796E-06	Reject H_0
	15 one-minute	0.716483516	Random	0.465934066	13.31354612	4.92136E-17	Reject H_0
	30 one-minute	0.671823722	Random	0.481481481	14.99600066	3.87001E-20	Reject H_0
	45 one-minute	0.672734468	Random	0.464582509	21.94048894	9.04759E-30	Reject H_0
15 Minutes	5 one-minute	0.523187908	Random	0.423565785	9.810582416	3.78346E-13	Reject H_0
	15 one-minute	0.731663685	Random	0.479427549	20.05285831	9.17915E-28	Reject H_0
	30 one-minute	0.672222222	Random	0.479059829	18.50982871	5.14588E-26	Reject H_0
	45 one-minute	0.705392810	Random	0.469374168	23.27314873	4.17127E-31	Reject H_0
30 Minutes	5 one-minute	0.520529071	Random	0.428492698	9.510315437	1.92900E-13	Reject H_0
	15 one-minute	0.643268124	Random	0.450326045	14.08193603	2.27841E-20	Reject H_0
	30 one-minute	0.631189264	Random	0.439379917	16.82178208	5.59662E-24	Reject H_0
	45 one-minute	0.659565024	Random	0.489125610	18.53091232	4.86254E-26	Reject H_0
45 Minutes	5 one-minute	0.536866359	Random	0.426267281	10.34072929	8.83648E-15	Reject H_0
	15 one-minute	0.595289079	Random	0.443254818	12.94505652	9.42814E-19	Reject H_0
	30 one-minute	0.626232742	Random	0.463017751	15.42911859	3.41548E-22	Reject H_0
	45 one-minute	0.644553073	Random	0.478351955	17.40698548	1.06317E-24	Reject H_0

To validate the robust performance of our proposed method, we conducted 30 repetitions of experiments each year over the past five years, yielding the following average results. The findings reveal that, in the subsequent years, the accuracy consistently remained above 60%, reaching its peak at 68.68% in 2018. This enduring trend underscores the reliability and effectiveness of our method. We observe stable performance across different market scenarios. For a detailed analysis of the experimental results, including total profit, transaction volume, and average profit, please refer to Table 8. This in-depth analysis once again emphasizes the universality of our method and its potential as a valuable tool in financial decision-making.

The objective of this study is to demonstrate the presence of discernible forces in the market influencing stock price trends. Successful statistical tests establishing the experimental group model's superior overall performance compared to the control group-random trading model would substantiate the argument that stock prices do not follow a random walk.

Abiding by the central limit theorem, the distribution of the sample average closely resembles that of a normal distribution. This occurs when the sample size exceeds 30. However, given the unknown overall variance, this study utilizes a T-test to scrutinize the hypothesis concerning the disparity between the averages of two populations. Although the T-test is suitable for populations with potentially distinct variances, it necessitates distinct test formulas. Therefore, it becomes imperative to verify the equality of the two population variances before executing the independent sample T-test, thereby ensuring the accuracy and reliability of the statistical analysis conducted in this study. The F distribution is employed to assess the null hypothesis $H_0 : \sigma_X^2 = \sigma_Y^2$ and the alternative hypothesis $H_1 : \sigma_X^2 \neq \sigma_Y^2$. The outcome of this examination dictates the selection of the appropriate T-test formula. Employing a significance level of 0.025 for evaluating the equality of variances, the statistical F-test results are delineated in Table 9. Following the assessment of overall variance equality, both the test and control groups underwent T-test analyses.

The T-test was employed to conduct a hypothesis test, examining whether the accuracy of the experimental group surpassed that of the control group, with the null hypothesis as the benchmark. If $H_0 : \mu_X \leq \mu_Y$, the accuracy of the experimental group is less than or equal to the accuracy of the control group, and if $H_1 : \mu_x > \mu_Y$, the accuracy of the experimental group is higher than the accuracy of the control group. As indicated in Table 10, the comparison of accuracy between the experimental group and the control group yielded a significance level below 0.05, signifying the rejection of the null hypothesis. The T-test results confirm the experimental neural network model's superior accuracy compared to the control, specifically the random trading model. This affirms the presence of observable forces in the market that impact its directional trends. The findings further emphasize the market's departure from conforming to the hypothesis of a random walk.

V. CONCLUSION

In summary, this research has delved into the intricacies of day trading in Taiwan's weighted index futures against the backdrop of a dynamically changing global economic landscape. The study sought to address the challenges posed by increased market volatility and overnight risks, offering a nuanced approach to intraday trading.

The incorporation of a neural network architecture, combined with a daily market activity structure, has demonstrated promising results in predicting intraday market movements. The developed model showcased notable accuracy, surpassing the random walk theory employed by the control group. This suggests that the proposed methodology holds potential in identifying lower-risk entry points within the intraday market, thereby assisting investors in managing risks and capitalizing on profit opportunities.

By contrasting theories such as the Random Walk Hypothesis with the Market Logic Theory, this research has provided a thorough comprehension of the elements shaping short-term fluctuations in stock prices. The daily market observations using Market Profile, especially through Time, Price, and Opportunities (TPO) charts, facilitated the identification of crucial market parameters necessary for formulating features in the neural network model.

The introduction of dynamic physical behavior and data normalization, coupled with resilient propagation (Rprop) as a supervised learning heuristic, enhanced the reliability and effectiveness of the model. Experimental results across various holding times consistently demonstrated high accuracy, with the 15-minute holding duration emerging as particularly promising.

Over a five-year period, the methodology showcased robustness and reliability, consistently outperforming the control group. Statistical analyses, including T-tests, substantiated the significant difference in accuracy between the experimental and control groups, challenging the notion of a random walk in the market.

In conclusion, the integration of artificial intelligence, specifically neural networks, with market logic presents a compelling avenue for decision support in intraday trading. This research contributes valuable insights to the field, offering a sophisticated framework for navigating the complexities of intraday trading in dynamic financial markets. Future research endeavors could further refine and expand upon this model, fostering advancements in the understanding and application of AI in financial market analysis.

REFERENCES

[1] M. Mazur, M. Dang, and M. Vega, "COVID-19 and the March 2020 stock market crash. Evidence from S&P1500," *Finance Res. Lett.*, vol. 38, Jan. 2020, Art. no. 101690.

[2] M. P.-B. Tran and D. H. Vo, "Asia–Pacific stock market return and volatility in the uncertain world: Evidence from the nonlinear autoregressive distributed lag approach," *PLoS ONE*, vol. 18, no. 5, May 2023, Art. no. e0285279.

[3] K.-T. Tsai, J.-S. Lih, and J.-Y. Ko, "The overnight effect on the Taiwan stock market," *Phys. A, Stat. Mech. Appl.*, vol. 391, no. 24, pp. 6497–6505, Dec. 2012.

[4] E. F. Fama, "Agency problems and the theory of the firm," *J. Political Economy*, vol. 88, no. 2, pp. 288–307, Apr. 1980.

[5] J. P. Steidlmayer, *Markets and Market Logic*. Chicago, IL, USA: Porcupine Press, 1984.

[6] B. Graham, D. L. Dodd, and S. Cottle, *Security Analysis Principles and Techniques*, 4th ed. New York, NY, USA: McGraw-Hill, 1962.

[7] J. Firich, "Futures trading based on market profile day timeframe structures," in *Proc. 1st WSEAS Int. Conf. Finance, Accounting Auditing*, 2012, pp. 80–85.

[8] C.-C. Chen, Y.-C. Kuo, C.-H. Huang, and A.-P. Chen, "Applying market profile theory to forecast Taiwan index futures market," *Exp. Syst. Appl.*, vol. 41, no. 10, pp. 4617–4624, Aug. 2014.

[9] M.-C. Wu, B. W. Yang, C. H. Lin, Y. H. Huang, and A. P. Chen, "Data mining application to financial market to discover the behavior of entry point—A case study of Taiwan index futures market," in *Harmony Search Algorithm*. Berlin, Germany: Springer, 2016, pp. 295–303.

[10] W.-Y. Huang, A.-P. Chen, Y.-H. Hsu, H.-Y. Chang, and M.-W. Tsai, "Applying market profile theory to analyze financial big data and discover financial market trading behavior—A case study of Taiwan futures market," in *Proc. 7th Int. Conf. Cloud Comput. Big Data (CCBD)*, Taiwan, Nov. 2016, pp. 166–169.

[11] M. Riedmiller and H. Braun, "A direct adaptive method for faster backpropagation learning: The RPROP algorithm," in *Proc. IEEE Int. Conf. Neural Netw.*, Mar. 1993, pp. 586–591.

[12] N. A. Setiawan, P. A. Venkatachalam, and A. F. M. Hani, "Diagnosis of coronary artery disease using artificial intelligence based decision support system," 2020, *arXiv:2007.02854*.

[13] S. Adikari and K. Dutta, "Identifying fake profiles in LinkedIn," 2020, *arXiv:2006.01381*.

[14] R. P. S. Hermanto and A. Nugroho, "Waiting-time estimation in bank customer queues using RPROP neural networks," *Proc. Comput. Sci.*, vol. 135, pp. 35–42, Jan. 2018.

[15] M. Shastri, S. Roy, and M. Mittal, "Stock price prediction using artificial neural model: An application of big data," *EAI Endorsed Trans. Scalable Inf. Syst.*, vol. 6, no. 20, pp. 12–16, 2019.

[16] D. Jothimani and S. S. Yadav, "Stock trading decisions using ensemble-based forecasting models: A study of the Indian stock market," *J. Banking Financial Technol.*, vol. 3, no. 2, pp. 113–129, Oct. 2019.

[17] S. A. Mitilineos and P. G. Artikis, "Forecasting of future stock prices using neural networks and genetic algorithms," *Int. J. Decis. Sci., Risk Manag.*, vol. 7, no. 1, pp. 2–25, 2017.

[18] A.-P. Chen and Y.-C. Hsu, "Dynamic physical behavior analysis for financial trading decision support [application notes]," *IEEE Comput. Intell. Mag.*, vol. 5, no. 4, pp. 19–23, Nov. 2010.

[19] J. Heaton, "Encog: Library of interchangeable machine learning models for Java and C#," *J. Mach. Learn. Res.*, vol. 16, pp. 1243–1247, Jun. 2015.

[20] G. Zhang, B. E. Patuwo, and M. Y. Hu, "Forecasting with artificial neural networks: The state of the art," *Int. J. Forecasting*, vol. 14, no. 1, pp. 35–62, 1998.

[21] P. C. Davies, "Design issues in neural network development," *Neurovest J.*, vol. 5, no. 1, pp. 21–25, 1994.

[22] M. Kearns, "A bound on the error of cross validation using the approximation and estimation rates with consequences for the training-test split," in *Proc. Adv. Neural Inf. Process. Syst.* Cambridge, MA, USA: MIT Press, 1996, pp. 1–7.

MIN-CHIH HUNG received the M.S. degree from the Institute of Information Management, National Chiao Tung University, Hsinchu, Taiwan, in 2013. He is currently pursuing the Ph.D. degree with the Institute of Information Management, National Yang Ming Chiao Tung University, Hsinchu. His research interests include machine learning, financial technology, and information.

AN-PIN CHEN received the Ph.D. degree in industrial and systems engineering from the University of Southern California. He currently serves as a Chair Professor with the Department of Finance, Asia University, Taiwan. His research focuses on finance decision support systems, data mining, financial engineering, knowledge management, and computational intelligence applications in finance. In 2020, he was honored as a Fellow of the Chinese Society for Management of Technology.

WAN-TING YU is currently pursuing the master's degree with the Institute of Information Management, National Yang Ming Chiao Tung University. Her research interests include digital finance, intelligent data analysis, and information-related fields.