ICIC Express Letters
Volume **17**, Number **8**, August **2023** ISSN 1881-803X
pp. **937–946**

CONSTRUCTION OF AUTOMATED TRADING SYSTEMS WITH PARAMETER SELECTION IN FINANCIAL MARKETS

Junko Shibata[1,*], Antonio Oliveira Nzinga Rene[2], Eri Domoto[3] and Koji Okuhara[2]

[1]Faculty of Economics
Kobe Gakuin University
518 Arise, Ikawadani-cho, Nishi-ku, Kobe, Hyogo 651-2180, Japan
*Corresponding author: shibata@eb.kobegakuin.ac.jp

[2]Faculty of Engineering
Toyama Prefectural University
5180 Kurokawa, Imizu, Toyama 939-0398, Japan
{ rene; okuhara }@pu-toyama.ac.jp

[3]Department of Media Business
Faculty of Media Business
Hiroshima University of Economics
5-37-1 Gion, Asaminami, Hiroshima-shi, Hiroshima 731-0192, Japan
er-domo@hue.ac.jp

Received December 2022; accepted February 2023

Abstract. *In recent years, the development of communication and information technology has increased the number of participants in financial markets and the liquidity of financial markets. As a result, many traditional trading rules obtained by financial market factors calculate past market technical indicators and predict future market movements based on the movements of the indicators. In this study, we analyze the market, consider other markets' impact on the foreign exchange market, and propose a method to select candlestick chart time and use the appropriate data for each period. Finally, we show by numerical experiments with real historical market data that the proposed method of selecting the optimal time is more profitable, taking account of the effects among several markets, and demonstrate its effectiveness.*
Keywords: High frequency data, Granger causality test, Candlestick chart time

1. **Introduction.** Since the birth of Foreign Exchanger (FX) with the complete liberalization of foreign exchange margin trading in 1996, the financial market's size has been expanding yearly. The development of information and communication technology and advances in financial engineering have increased the number of participants in financial markets by reducing the size of trading units, lowering transaction fees, and increasing the liquidity of financial markets by simplifying and speeding up transactions. These factors brought more liquidity and more market participants to the foreign exchange market, transforming the initially sizeable foreign exchange market into an even larger market [1].

The large amount of financial time series data generated has analyzed using time series analysis approaches and other methods [2]. Furthermore, the test of efficiency has discussed based on empirical studies of efficiency in the foreign exchange market [3]. With the development of information and communication technology, it has become possible to trade according to automatic rules by making full use of computer performance [4]. Recently, there are also researches on the introduction of artificial intelligence to obtain price forecasts and strategies [5].

DOI: 10.24507/icicel.17.08.937

The analysis results obtained by financial market factors are used as criteria for conventional investment decisions. However, since these analyses predict future market trends by calculating indicators based on past market movements [6], they may not match current market movements. Technical analysis is the method of analyzing the future market by analyzing price fluctuations and movement cycles based on information obtained from the market. On the other hand, fundamental analysis is to predict the future market by analyzing economic indicators released by each country, economic news, and statements made by people who can influence the economy [7]. As the market has expanded in size, a variety of analytical methods have appeared [8]. Although there exist studies that analyze the impact of the foreign exchange market on other markets or examine the impact of other markets on the foreign exchange market, few studies consider such information when trading in the foreign exchange market.

In this study, we analyze the market and consider other markets' impact on the foreign exchange market when trading. As a result, we propose a method that can respond not only to analytical results obtained from internal market factors but also to fluctuations that cannot be predicted from those factors. Previous studies have used only one type of candlestick chart time data, representing market price movements over a certain period. Specifically, we propose an analysis method for automated foreign exchange trading using the Granger Causality Test, which identifies causal relationships among multiple time series in the Vector Autoregressive Model (VAR), a representative model for time series analysis.

First, we obtain real-time, high frequency data from exchange trading platforms and accumulate these data to create historical data for analysis. Next, we extract the parameters that give the indicator the highest evaluation value in each historical data generated, compare the evaluation values calculated by each historical data, and select the best historical data to make a buy or sell decision for the market. The same analysis is performed for other markets, and a buy/sell decision is made for that market. By Granger causality testing between other markets and the exchange market, we create a market forecasting system that considers intra-market factors and extra-market influences by selecting data from other markets for trading and actual trading. The effectiveness of the proposed method is verified by conducting real-time trading using the proposed automated trading system with a demo account. Finally, we demonstrate the effectiveness of the proposed method by comparing the final trading results between the proposed automated trading system and the same period.

2. High Frequency Data Collection.

2.1. Trading platforms.
The trading platform we use in this study is Meta Trader 5 (MT5). MT5 is a free application for traders who perform technical analysis and trading operations in FX. It is currently one of the world's most popular trading platforms, allowing for trading operations on various markets, such as FX and stock trading. Many FX operators also use it with users because it can display charts in various time frames to see the movement of market fluctuations. In addition, it is loaded with technical analysis and automated trading tools called EA used in market analysis.

MT5 can open a demo account and perform realistic trading. Using Python, one can simulate trading on MT5 by acquiring tick data from MT5 and sending trading orders.

2.2. Technical analysis using indicators.
The FX indicators are analytical methods that predict future prices based on factors such as past prices and the amount of volume. They are used for methods such as day trading and scalping that aim for profits in short-term trades. In addition, historical data is often used in technical analysis because the analysis targets factors within the market and factors by issue.

The information used in technical analysis is the current market trend, its strength, and the turning point of the trend. Recently, research has been conducted on neural networks and machine learning, which can predict data, analyze from large-scale data, and calculate optimal technical indicators for effective forecasting [9].

The FX indicator calculates information on exchange rates and uses it to make buying and selling decisions. Using indicators makes it possible to discover information that cannot be seen by human eyes alone. There are two types of indicators: oscillators and trend indicators. Exchange rates tend to fall when they rise too much and rise when they fall too little. Oscillator indicators take advantage of this property to show when an exchange rate is rising or falling too much, either numerically or graphically.

2.3. **Back test and optimization in strategy testers.** The back test is the simulation of trading rules with historical market information using a tool to confirm whether the trading rules are effective or not. The trading rule that is currently effective may be profitable but may be unprofitable if run for more extended period. One way to resolve this concern is the backtest, which can confirm the validity of trading rules. Some FX indicators used in trading rules require parameters to be set, such as the period to be used in the calculation. Normally, the FX indicator is calculated using pre-defined parameters and applied to the trading rules. In reality, there may be parameters that are more optimal than those parameters. We then tune the optimal parameters by the backtest and use the selected parameters to perform automated trading. This study uses Backtesting.py, which performs trading simulations using collected data, and TA-Lib, which calculates representative indicators in technical analysis.

3. Granger Causality Test and Chart Time.

3.1. **Selection and utilization of market data.** In this study, we use a VAR model to analyze 9 variables: the yen-dollar exchange rate, the Nikkei Stock Average, the New York Dow Jones Industrial Average, gold, crude oil, copper, the British pound-yen exchange rate, the British stock index 100 and the euro-yen exchange rate.

The VAR(ρ) model assumes $\boldsymbol{y_t}$ as a constant and regresses it on the past values of its own ρ period, and is expressed as follows:

$$\boldsymbol{y_t} = \boldsymbol{c} + \Phi_1 \boldsymbol{y_{t-1}} + \cdots + \Phi_\rho \boldsymbol{y_{t-\rho}} + \varepsilon_t, \quad \varepsilon_t \sim W.N.(\Sigma) \tag{1}$$

where $\boldsymbol{c}$ is an $n \times 1$ constant vector and Φ_i is an $n \times n$ coefficient matrix. ε_t is the vector white noise of the variance-covariance matrix. Specifically, a VAR model with two variables, x_t and y_t, is expressed as follows:

$$x_t = a_1 x_{t-1} + a_2 x_{t-2} + a_3 y_{t-1} + a_4 y_{t-2} + u_{xt} \tag{2}$$

$$y_t = b_1 x_{t-1} + b_2 x_{t-2} + b_3 y_{t-1} + b_4 y_{t-2} + u_{yt} \tag{3}$$

The last order in this case is 2 and u is the disturbance term.

In this experiment, we performed a unit root test and cointegration test on 9 variables obtained in real time (the yen-dollar exchange rate, the Nikkei Stock Average, the New York Dow Jones Industrial Average, gold, crude oil, copper, the British pound-yen exchange rate, British stock index 100 and the euro-yen exchange rate). We then used these variables to estimate a VAR model. We performed a Granger Causality Test to analyze the relationship between real-time data to determine whether other markets can be used to predict real-time fluctuations in the yen-dollar exchange rate.

3.2. **Utilization of other markets through causal relationships.** The Granger Causality Test is performed after the necessary processing of the data to be used. The Granger Causality Test was proposed in 1969 based on the idea that it would be useful to have a concept that could determine the existence of causality from time series data alone. The Granger Causality Test is defined as follows [10].

The Granger Causality Test

One can predict future x based only on current and past x values and compare the predicted x values based on current and past x and y. If the latter's Mean Squared Error (MSE) is small, then it is said there exists the Granger causality from y_t to x_t.

The Granger Causality Test shows that one variable x affects another variable y in a time series model. More specifically, the past value of y has explanatory power for the variation of x, holding other conditions. That is different from causality in the logical sense of the term. The Granger Causality Test can also be easily extended to the general case of multiple variables.

General Granger Causality Test

Assume that $\boldsymbol{x_t}$ and $\boldsymbol{y_t}$ are vector processes. Also, let Ω_t denote the set of available information at t. Then, $\widetilde{\Omega}$ is Ω_t minus present and past $\boldsymbol{y}$. At this time, the prediction of future $\boldsymbol{x}$ based on $\widetilde{\Omega_t}$ and comparing the future $\boldsymbol{x}$ based on Ω_t, if the MSE of the latter is smaller than Granger causality from $\boldsymbol{y_t}$ to $\boldsymbol{x_t}$ is said to exist. Note that the MSEs are large and small in the matrix sense. Next, we illustrate these multivariate Granger causality analyses using the bivariate VAR(2) model. The bivariate VAR(2) model is expressed as follows:

$$\begin{cases} y_{1t} = c_1 + \phi_{11}^{(1)} y_{1,t-1} + \phi_{12}^{(1)} y_{2,t-1} + \phi_{11}^{(2)} y_{1,t-2} + \phi_{12}^{(2)} y_{2,t-2} + u_{1t} \\ y_{2t} = c_2 + \phi_{21}^{(1)} y_{1,t-1} + \phi_{22}^{(1)} y_{2,t-1} + \phi_{21}^{(2)} y_{1,t-2} + \phi_{22}^{(2)} y_{2,t-2} + u_{1t} \end{cases} \tag{4}$$

When $\phi_{12}^{(1)} = \phi_{12}^{(2)} = 0$, there is no Granger causality from y_{2t} to y_{1t}. In general, the absence of Granger causality means that in the VAR y_1, the coefficients on y_2 are all zero, and no change can be seen in the prediction of y_1 by considering past values of y_2. Therefore, in the VAR framework, the Granger Causality Test can be performed using the F test. Specifically, to perform the Granger Causality Test, we need to test H_0: $\phi_{12}^{(1)} = \phi_{12}^{(2)} = 0$.

That is, the following equation is estimated by Ordinary Least Squares regression (OLS) and the residual sum of squares is SSR_1.

$$y_{1t} = c_1 + \phi_{11}^{(1)} y_{1,t-1} + \phi_{12}^{(1)} y_{2,t-1} + \phi_{11}^{(2)} y_{1,t-2} + \phi_{12}^{(2)} y_{2,t-2} + u_{1t} \tag{5}$$

Next, the following model with constraints is then estimated by OLS and the residual sum of squares is SSR_0.

$$y_{1t} = c_1 + \phi_{11}^{(1)} y_{1,t-1} + \phi_{11}^{(2)} y_{1,t-2} + u_{1t} \tag{6}$$

The F statistic is defined as follows.

$$F \equiv \frac{SSR_0 - SSR_1/r}{SSR_1/(T - n\rho - 1)} \tag{7}$$

Since $2F$ asymptotically follows $\chi^2(2)$, the value of $2F$ is compared to the 95% point of $\chi^2(2)$. If $2F$ is larger, we reject the null hypothesis that there is no Granger causality from y_{2t} to y_{1t}. We can then conclude that y_{2t} can be used to predict y_{1t}.

In general, the flow of the Granger Causality Test on an n-variate VAR(ρ) is as follows.

Procedure for Granger Causality Test in $\boldsymbol{n}$ variable VAR($\boldsymbol{\rho}$)

1) The model of y_{kt} in the VAR model is estimated by OLS, and the residual sum of squares is SSR_1.
2) The constrained model for y_{kt} in the VAR model is estimated by OLS, and the residual sum of squares is SSR_0.
3) Compute the F statistic with $F \equiv \frac{SSR_0 - SSR_1/r}{SSR_1/(T-n\rho-1)}$, where r is the number of constraints needed for the Granger Causality Test.
4) Comparing rF with the 95% point of $\chi^2(r)$, if rF is larger, Granger causality from a variable to y_{kt} exists, if it is smaller, Granger causality does not exist.

We check whether the Nikkei Stock Average, the New York Dow Jones Industrial Average, and gold were causally related to the yen-dollar exchange rate market from October 25, 2021, to October 26, 2021 (see Figure 1). As mentioned earlier, a cointegration test was conducted after the unit root test, and a Granger causality test was conducted for markets that were found to have no cointegration relationship with the yen-dollar market. We also programmed variance and impulse response functions that can be analyzed using the VAR model. Then, we check whether there is Granger causality with the yen-dollar market.

```
Granger causality F-test. H_0: us30 does not Granger-cause tick. Conclusion: fail
to reject H_0 at 5% significance level.
===============================================
Test statistic Critical value p-value      df
-----------------------------------------------
      0.5199           1.298   1.000 (68. 34636)
-----------------------------------------------

Granger causality F-test. H_0: jp225 does not Granger-cause tick. Conclusion: fail
to reject H_0 at 5% significance level.
===============================================
Test statistic Critical value p-value      df
-----------------------------------------------
      0.8902           1.298   0.728 (68. 34636)
-----------------------------------------------

Granger causality F-test. H_0: gold does not Granger-cause tick. Conclusion: fail
to reject H_0 at 5% significance level.
===============================================
Test statistic Critical value p-value      df
-----------------------------------------------
      0.7074           1.298   0.968 (68. 34636)
-----------------------------------------------
```

Figure 1. Granger causality test

The results obtained from the analysis are shown in Figure 2. We confirm that the Nikkei Stock Average and gold are the two markets with Granger causality concerning the yen-dollar exchange rate market during this period. The analysis of variance shows that the contribution of gold and the Nikkei Stock Average is higher than that of the New York Dow Jones Industrial Average. Furthermore, the contribution increases in proportion to the length of the forecast period, suggesting that it may take some time before the change is included in the yen-dollar change. These results confirm that other markets can be used to forecast changes in the yen-dollar exchange rate. Therefore, the Granger Causality Test is also used in the proposed method to examine the inter-market relationship between the yen-dollar exchange rate and other markets.

3.3. **Selection of candlestick chart time.** In this study, the characteristics of fluctuations during market hours were extracted, and trades were conducted during the hours when profits are likely to increase based on the obtained characteristics. In this experiment, we test the effects of the day of the week and time of day using data from the yen-dollar exchange rate from November 1, 2021, to December 1, 2021.

FX candlestick chart is an essential yardstick for observing market changes. Since each time frame has its characteristics, multiple time-frame analysis is sometimes used to analyze trends by looking at multiple time frames when trading. Long-term data such as four-hourly, daily, and weekly data are said to have continuity and strong momentum. In trading, when long-term data is in a downtrend, the uptrend is absorbed by the long-term data even if the short-term data is in an uptrend, such as 1-minute or 10-second data. Therefore, it is better to check the long-term time frame.

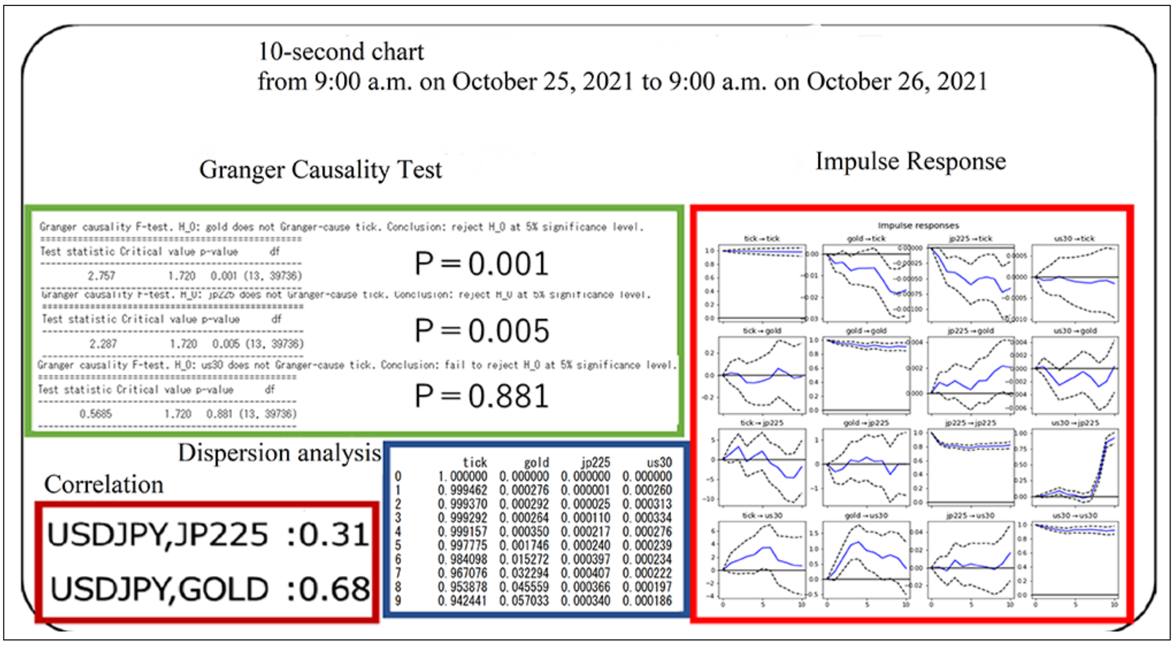

FIGURE 2. Results of analysis performed on each market

In studies proposing conventional automated trading, these periods are predetermined. Many studies attempt to increase profitability by selecting indicator parameters and combining multiple rules. The proposed program does not automatically select the optimal hourly data in the real-time market. This fact implies that using multiple period data may yield better results than using single period data to predict future market movements and obtain trading strategies. This is because it is possible to obtain the most optimal trading strategy in the real-time market concerning the time of day. For this reason, the proposed method prepares multiple time frames of short-term data and performs the backtest using the optimized parameters of the indicator for each time frame. The trading rule is selected by comparing the results by selecting the optimal time frame data for that period.

3.4. **Parameter selection and causality derivation.** In this study, the latest tick data is obtained from the market moving in real time, accumulated, and then resampled at a specified time frame. This allows historical data from recent price movements to be used for indicator parameter selection and indicator and stock selection. The indicator parameters are thereafter optimized using the optimized historical data. The flow from historical data generation to indicator parameter optimization is shown below.

1) Retrieve tick data from MT5 for each tick data update
2) Store tick data only once per second and store it in a data frame
3) Resample in the form of OHLCV in the specified time interval and save to CSV file
4) Optimize indicator parameters using created historical data
5) Save optimized parameters to CSV file

The first step is to obtain tick data from MT5. The acquisition is made in Python. The MT5 used in the experiment has a module for exchanging data using Python [11]. Indicator calculations require volume values in addition to price data. Therefore, the volume value contained in the stored tick data is used.

There are three data frames to be saved: time, price, and volume, as shown in Table 1. Saved data frames continue accumulating as long as the program runs, but when the program runs again, all the collected tick data are reset. To avoid this, we save each additional tick data in a CSV file and read the CSV file at the beginning of the program so that we can continue to use the previous data.

Table 1. Format of stored tick data

	Time	Price	Volume
0	2021/9/24 12:21	110.40595	1
1	2021/9/24 12:21	110.409	1
2	2021/9/24 12:21	110.4095	1
3	2021/9/24 12:22	110.4105	1
4	2021/9/24 12:22	110.413	1

The saved data set is written to be updated to the latest one each time resampling is performed. After the historical data is generated, the data is used to optimize the indicator parameters. This study uses the Backtesting.py library, which allows backtesting in Python. In addition, the TA-Lib library, which provides historical data and numerical values such as the period required for each indicator, is used for indicator calculations. Combining TA-Lib with backtesting allows using each indicator for a given period and obtaining the results of trades during such period. The parameter with the best evaluation index is the optimized parameter by comparing the resulting evaluation index for all combinations of the specified parameters. In backtest, trading rules are set for each indicator, and orders are sent when the buy or sell timing occurs. At that time, the profit and loss limits are sent simultaneously, and settlement is made when the price has moved by the respective limits.

3.5. **Algorithm of the proposed method.** In this experiment, the optimal parameters for each period are calculated from backtests using the three types of historical data created and saved in a CSV file to select the optimal historical data for each period automatically. Here, an example of the historical data generated is shown in Table 2. We use the stored optimal parameters for each period to derive a valuation indicator. The optimum period for each indicator can be selected by comparing the evaluated indicator calculated for each period. The historical data for the optimal number of time charts selected for each indicator is used as the historical data for that market. The optimal historical data for each market and the parameters of each indicator are selected by evaluating each market.

Table 2. Example of the generated historical data

Time	Open	High	Low	Close	Vol.
9/24 12:21:30	113.672	113.682	113.671	113.678	13
9/24 12:21:40	113.6795	113.6885	113.6785	113.6885	13
9/24 12:21:50	113.691	113.699	113.688	113.691	14
9/24 12:22:00	113.6915	113.6975	113.689	113.6975	12
9/24 12:22:10	113.6985	113.742	113.6985	113.7285	16

In actual automated trading, the indicators for each market are divided according to the conditions, as shown in Figure 3. In the chart, light gray indicates a buy signal in the yen-dollar market, and dark gray indicates a sell signal in the yen-dollar market. The lack of color indicates that the market does not have Granger causality for the yen-dollar exchange rate. Otherwise, it is a case where Granger causality is present, but the value of the correlation does not satisfy the condition. Thus, Granger causality and correlation can be used to set the terms of the transaction and utilize causality and correlation in the transaction.

EMA1	EMA2	BBAND	MACD1	MACD2	MACD3	RSI	STOCH1	STOCH2	DMI	TrendLINE
6	20	5	10	22	11	8	5	3	12	300

	EMA	BBAND	MACD	RSI	STOCH	DMI	LINE
usdjpy	0	0	0	0	0	0	0
gold	0	-1	0	0	0	0	0
jp225	-1	-1	1	0	0	0	0
us30	1	0	0	0	0	0	0
oil	1	0	0	0	0	0	0
corn	0	-1	0	0	0	0	0
eu50	-1	0	1	0	0	0	0
gbpjpy	-1	-1	1	0	-1	0	0
eurusd	1	0	-1	0	-1	0	0

FIGURE 3. Summary of causality and correlation for each market

4. **Numerical Experiments and Consideration.** The numerical experiments in this study consist of five processes as follows:

1) Data acquisition and historical data generation
2) Indicator parameter optimization
3) Granger causality test for the yen-dollar exchange rate
4) Rule selection using Granger causality on the optimal period
5) Automatic trading with the optimal rules

We assume that Model 1 is a trading method using only the indicators of the yen-dollar market, Model 2 is a trading method using the indicators of the yen-dollar market and other financial markets, and Model 3 is the proposed method. The effectiveness of the proposed method is demonstrated by comparing the final evaluative indicators of the three transaction methods and by subjecting each transaction to some tests.

The results of this experiment are as follows: The trading method using only the indicator for the yen-dollar market had 268 trades, a 49% winning rate, and a balance of -4135 yen. The trading method using the indicator for the yen-dollar market and other financial markets had 162 trades, a 39% winning rate, and a balance of -2621 yen. Finally, the proposed method had 240 trades, a 52% winning rate, and a balance of $+8265$ yen.

The evaluation indicators, including the amount of money traded, are shown in Table 3. The Profit Factor (PF), one of the evaluation indicators, expresses the ratio of total profit to total loss and can be calculated as the quotient of total profit divided by the total loss. If the total profit exceeds the total loss, the PF is greater than 1. Therefore, the proposed method has a value of 1.1. In contrast, the trading method using only the indicator for the yen-dollar market, and the trading method using the indicator for the yen-dollar market and other markets have values less than 1. Therefore, as seen from the figure, the total profit is less than or equal to the total loss. Since the PF of the proposed method exceeds 1, we can assume that a similar program running for a similar period as this would make a profit of 1.1 times the loss.

The Recovery Factor (RF), also called the risk-return ratio, is an evaluation indicator that indicates the potential profit of an automated trading program, i.e., how much profit can be expected about losses. The higher the value of RF, the greater the likelihood

TABLE 3. Each evaluation indicator for the same time period

	Balance of payments	PF	RF	EXP
Model 1	-4135 yen	0.96	-0.71	-16.18
Model 2	-2621 yen	0.89	-0.45	-15.43
Proposal method	$+8265$ yen	1.1	2.04	34.44

that a significant profit can be obtained with less risk. The RF can be calculated as the quotient of the net profit divided by the maximum drawdown. For example, the value of the proposed method is 2.04. Therefore, the automatic trading program based on the proposed method can be expected to be profitable if it continues to operate in the market in the future. On the other hand, the trading method using only the indicator for the yen-dollar market and the indicator for the yen-dollar market and other markets had negative values, indicating that no profit is expected in the future. A system operating for only a short period includes the possibility of a negative value when the system is operated for a long period. Therefore, the value of RF obtained after a short period is an evaluation indicator that can be used to imagine the results of a more extended period. The RF value indicates that a profit is expected when the automated trading program based on the proposed method is run for a longer period than the current one.

Expectancy (EXP) is an evaluation index calculated as the quotient of the total profits and losses divided by the total number of trades and represents the amount of profit and loss that can be expected from a single trade. A comparison of the models shows that the proposed method can expect to earn +34.44 per trade. The other two methods will likely have a negative profit and loss per trade. As can be seen from the number of trades, the proposed method is a system that aims to make a profit by making multiple trades. Therefore, the fact that +125 can be expected from a single trade indicates that the system is making optimal trades. From these indicators, it can be concluded that the trading method of selecting the optimal period, considering the influence between markets, is a profitable trading method.

Of the seven indicators used in this study, four were oscillators. The oscillator-type indicators are characterized by the fact that they generate buy and sell signals for contrarian trades. On the other hand, the trend-type indicator is characterized by producing buy and sell signals for forwarding trading. The figure in the price of possession in Model 1 shows a large negative value. This was when the price showed a long uptrend, and many oscillators gave sell signals in the contrarian market. Therefore, it may be more challenging to make a profit with the proposed method for trends formed over a long period than in other markets. Since oscillators and trend indicators have their own merits and demerits, changing the combination of the two may improve the performance. Further improvement is also expected in terms of indicator combinations. Specifically, as in this case, the most profitable combination at the time can be selected and used for trading.

5. Conclusion.

Most of the trading rules used in conventional research calculate technical indicators of past markets and predict future market movements based on the movements of the indicators. In addition, period data is essential in forex trading, and it is considered better to trade by observing multiple periods, such as multiple timeframe analysis. Therefore, previous studies used a single period and may not have looked at periods from multiple perspectives. No study created an automated trading program that considers not only the impact between markets but also the impact on other markets.

This study used Granger causality analysis to confirm that other markets have Granger causality to the yen-dollar exchange rate. Furthermore, by considering the relationship between these markets, the proposed method can trade in response to market price movements that cannot be predicted by using indicators based on historical data of the yen-dollar exchange rate. The method also allows trading with a multi-frame analysis that looks at the flow of multiple periods by having the program automatically select the best short-term period for the period. Numerical experiments have shown the effectiveness of the proposed method.

Future work is to improve the indicator combination. However, computer processing time is expected to increase due to the many processes required to find the optimal parameters. Therefore, it is necessary to devise a way to enable real-time processing.

REFERENCES

[1] K. Takahashi, A study on predictability of futures foreign exchange market, *Kwansei Gakuin Shogaku Kenkyu*, vol.62, pp.95-116, 2010.
[2] R. S. Tsay, *Analysis of Financial Time Series: Financial Econometrics*, Wiley-Interscience, 2001.
[3] Y. Takeuchi and T. Yamamoto, Testing efficiency in the foreign exchange market –An approach by time series analysis–, *Keizai Kenkyu*, vol.38, no.2, pp.97-109, 1987.
[4] T. Matsui and T. Goto, Acquiring and analyzing trading strategy in financial market using reinforcement learning, *Journal of the Japanese Society for Artificial Intelligence*, vol.24, no.3, pp.400-407, 1994.
[5] A. Nukui and T. Takagi, Proposal of FX system trade using AI, *Proc. of the National Conference of JASMIN 2019 Autumn*, pp.1-30, 2019.
[6] Y. Yajima, Long-memory models in time series analysis, *Ouyou Toukeigaku*, vol.23, no.1, 1996.
[7] T. Kanou, *Random Walkness and Fundamentals of Exchange Rates: A Perspective from Dynamic Stochastic General Equilibrium Analysis*, The Report of the 2012 Financial Research Study Group, 2013.
[8] J. Uchida and H. Anada, Construction of a foreign exchange trading strategy using genetic network programming by considering the technical index signal strength, *The 34th Annual Conference of the Japanese Society for Artificial Intelligence*, 2020.
[9] Y. Wang, A. C. De Castro and H. Kanoh, *Forex Trading Method Based on Majority Voting Strategy for Non-Inferiority Solution Sets Obtained by Multiobjective GA*, IPSJ SIG Technical Report, vol.26, pp.1-6, 2016.
[10] T. Okimoto, *Econometric Time Series Analysis of Economic and Financial Data*, Asakura Publishing Co., 2010.
[11] *MT5 Back Testing Methods OANDA FX/CFD Labeducation*, https://www.oanda.jp/lab-education/blog_mt5/auto_trading/mt5backtest/, Accessed on Dec. 25, 2021.
[12] J. Li, T. Zhou and X. Hu, Prediction algorithm of stock holdings of Hong Kong-funded institutions based on optimized PCA-LSTM model, *International Journal of Innovative Computing, Information and Control*, vol.18, no.3, pp.999-1008, 2022.