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Multi-objective optimization for algorithmic trading in the Vietnamese stock market

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ABSTRACT

This study aims to optimize algorithmic trading strategies using the relative strength index (RSI) and the moving average convergence divergence (MACD) indicators in the Vietnamese stock market. An automated trading system is constructed to optimize indicator parameters using multi-objective particle swarm optimization (PSO) over three objective functions: total return, win rate, and number of trades. The system employs simultaneous optimization of parameters and signal aggregation for developing the optimal selection strategy. Based on daily Vietnam index data from 2018 to 2024, the results show that the PSO method surpasses the differential evolution (DE) method in both returns and execution time. Additionally, the optimal selection strategy achieves superior performance compared to benchmark strategies. It also demonstrates the ability to adapt to the preferences of traders by selecting appropriate indicators. Traders can use the MACD indicator to seek higher profits, while the RSI indicator is more suitable for minimizing transaction costs in a volatile market.

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1. INTRODUCTION

Research in the field of finance, especially in trading, is always changing with updates and improvements in technology. Algorithmic trading, which involves feeding a computer predetermined mathematical rules to use to generate trading signals, has been presented in research for decades now [1]-[3]. Nonetheless, good algorithmic trading strategies are still in demand because of differences in performance metrics: Sharpe Ratio, maximum drawdown, win rate, profit factor, and Calmar ratio [4], [5]. In the process of developing trading strategies, technical indicators remain one of the important tools in understanding the dynamic nature of financial markets. However, choosing a suitable indicator from the million available indicators is indeed still a significant challenge [6]. Besides choosing an appropriate indicator, fine-tuning the parameters of these indicators is a crucial technique for developing an effective trading strategy. Optimization techniques that have been developed include grid search and random search, genetic algorithms [7]. Subsequently, Bayesian optimization [3] and reinforcement learning [8], [9] have been shown to outperform the formers.

Traditional algorithmic trading strategies have yielded many outstanding results, but only a single objective function, profit or risk, is chosen to optimize [10], [11]. This approach can lead to sub-optimal solutions because it ignores some important aspects of risk management. Traders are tasked not only with maximizing profits but also with controlling risks and ensuring profit distribution [12]; in essence, this is the definition of multi-objective optimization (MOO) in algorithmic trading. The MOO method enables the optimization of various objectives simultaneously, thus providing a more robust strategy design.

There are primarily two methods for solving the MOO problem: the scalarization technique and the Pareto approach [13]. For the scalarization method, different objective functions will be converted into one objective function through a scalar weight function. In which, the weight of each objective function will be determined in advance [14]. These weights refer to how relatively important each objective is; therefore, higher weights show greater relative priorities [15]. For the Pareto method, a set of solutions is identified where no objective can be improved without worsening another. This set, called the Pareto front, helps decision-makers balance trade-offs between conflicting objectives [16]. Deb *et al.* [17] demonstrated that the non-dominated sorting genetic algorithm II (NSGA II) algorithm can generate a set of optimal portfolios that balance risk and return. Multi-objective evolutionary algorithms is also applied in an attempt to optimize portfolio selection [18]; this evidences that including more than one objective could enhance decision-making. Studies on differential evolution (DE) algorithms have created a Pareto front for evaluating technical indicators [19], [20]. The main findings did not compare different optimization techniques but presented a diverse set of potential solutions for further analysis. For instance, in [21], the inclusion of optimal sets of parameters for the moving average convergence divergence (MACD) and the relative strength index (RSI) was done using multi-objective evolutionary algorithms. All of this underscores the need for further optimization of the algorithms with information derived from new data.

As an emerging market, the Vietnamese stock market is a good environment in which to research algorithmic trading strategies [22], [23]. This market is more volatile and risky compared to mature financial markets [24]. Thus, MOO is essential for algorithmic trading to accommodate the diverse risk preferences of traders in the Vietnamese market. Furthermore, the research results can be applied or compared to other international markets. In this study, we build upon and enhance previous research through the following approaches:

- The particle swarm optimization (PSO) method is applied to optimize multiple objectives simultaneously instead of using a weight vector as in previous studies
- An optimal selection strategy is proposed to aggregate signals after optimizing the parameters of multiple technical indicators
- The experiments are trained and tested based on the time series cross-validation method, which is suitable for backtesting trading strategies in the real market

More precisely, we construct an automated trading system that can select the best strategy with an optimized indicator for each training and testing period. This system uses multi-objective PSO to develop an optimal selection strategy over three objective functions: total return, win rate, and number of trades. The DE algorithm is considered as the baseline method for comparison. To evaluate performance using optimized settings for each indicator, experiments were conducted using 6 years of daily data from the VNINDEX. To test whether the chosen configuration of parameters will perform well in different scenarios. We use a time series split method to partition the data into several blocks. These blocks are then combined to form training and testing datasets. After analyzing the trade-offs between multiple objectives, the best indicator is selected for each period.

Our research makes several contributions. First, we provide insights into why PSO is a superior method for optimizing parameters for algorithmic trading strategies. Our results indicate that the PSO method outperforms the DE method in optimizing algorithmic trading strategies over both in-sample and out-sample data. With an execution time of 21 seconds for 1 year of daily data, the PSO method is suitable for traders with short-term trading purposes. This result is consistent with the findings in [1]. Second, the proposed optimal selection strategy can combine the advantages of the MACD and the RSI. The proposed strategy outperforms the single-objective optimization strategy and the default strategy in terms of average profit and win rate in both training and testing periods. These findings are consistent with results in previous studies [25]-[27]. Finally, the results from MOO by the PSO validate previous studies by demonstrating the effectiveness of combining different technical analysis indicators in building algorithmic strategies [28], [29]. Our proposed strategy can be used to exploit the strengths of both the MACD and the RSI. The results showed that both optimized MACD and optimized RSI can outperform their typical forms for all periods. The RSI strategy is chosen when the trader wants to gain a modest profit and minimize risks with highly volatile assets. Conversely, MACD is suitable for traders who desire more profit but are willing to assume high risk due to higher transaction costs.

The remainder of this paper is structured in the following manner. Initially, section 2 details the MOO algorithm for the indicators used in technical analysis. Subsequently, section 3 provides an overview of the experimental methodology, results, and a discussion of these findings. The paper concludes with section 4, which summarizes the results and suggests future research directions.

2. METHOD

In this section, we first introduce MOO in trading and describe the PSO algorithm. We then present a trading system, along with a description of its components and the implementation of the optimization algorithms.

2.1. Multi-objective optimization

MOO, a form of vector optimization, is widely utilized across various scientific domains such as engineering, economics, and finance. This approach is particularly valuable when making optimal decisions that involve navigating compromises among two or more competing objectives. The mathematical formulation of the MOO problem is presented as (1):

$$\min g(x) = \min_{x\in\mathcal{X}}\Big(g_1(x), g_2(x), ..., g_n(x)\Big), \tag{1}$$

where x is the solution, $\mathcal{X}$ is the feasible set, n is the number of functions ($n \geq 2$), and $g_j(x)$ is j^{th} objective function. Note that maximizing a certain objective function can be seen as the same as minimizing its negative counterpart.

Since we're optimizing for total return, win rate, and number of trades, we define a multi-objective fitness function $f(P_i)$ that evaluates a particle's performance based on these objectives:

$$f(P_i) = [f_{TotalReturn}(P_i), f_{Winrate}(P_i), f_{NumberOfTrades}(P_i)]. \tag{2}$$

2.2. Multi-objective particle swarm optimization

Introduced in 1995, PSO is a technique modeled on the social behaviors observed in natural swarms, such as birds, fish, or insects, particularly in their collective search for food [30]. PSO depends on a swarm of individual entities or particles, each moving through the multidimensional search space. The random initialization is done at some position, to which each particle is assigned a fitness value according to the fitness function that is being optimized. PSO is different from other optimization algorithms, such as genetic algorithms, differential evolution, and gradient descent, since it has very few hyperparameters and is not dependent on the gradient of the objective. Therefore, it is very efficient with a low computational cost and good results. In the trading environment, the PSO algorithm utilizes a population of particles, each representing a potential set of parameters for the combined strategy. In this paper, we consider two common technical indicators: RSI and MACD. Therefore, each particle i has a position vector P_i containing the parameters for both RSI and MACD:

$$P_i = [m_i, b_i^l, b_i^u, \psi_i, \rho_i, \phi_i], \tag{3}$$

where m is number of period in RSI, b^l and b^u are the lower and upper boundary in RSI; ϕ, ρ, and ψ are the number of of slow exponential moving average (EMA), signal line, and fast EMA in MACD, respectively. Each particle also has a velocity vector V_i that determines its movement in the search space.

In the iterative process, the velocities and positions of the particles get changed. The fitness value helps each particle identify its best local solution (p^{best}), which is then benchmarked against the swarm's best global solution (g^{best}) to refine the global optimum. The algorithm updates both the velocity (V) and position (P) of the particles according to specific rules designed below to guide the swarm toward optimal solutions.

$$V_i^{d+1} = \gamma V_i^d + \beta_1 w_1(p_i^{best} - P_i^d) + \beta_2 w_2(g^{best} - P_i^d) \tag{4}$$

$$P_i^{d+1} = P_i^d + V_i^{d+1} \tag{5}$$

where d is the current iteration, γ, β_1, and β_2 are the coefficients of the particle's inertia, the personal component, and the global component, respectively. Uniform distribution is applied to initialize positive random weights w_1 and w_2.

The parameter optimization algorithm using PSO is described in Algorithm 1. Next, the flowchart illustrating the PSO algorithm process is shown in Figure 1 to clarify the methodology and its application in optimizing trading parameters.

Algorithm 1. The PSO algorithm for parameter optimization

Initialization
for each particle i in a swarm population size I **do**
    Initialize P_i and V_i randomly
    Evaluate the fitness $f(P_i)$ according to Eq. (2)
    Initialize p_i^{best} with a copy of P_i
end for
Initialize g^{best} with the best fitness
Set $d \leftarrow 0$
Repeat until a stopping criterion d_{max} is satisfied
while $d < d_{max}$ **do**
    for each particle i in I **do**
        Update V_i^d and P_i^d according to Eqs. (4) and (5)
        Evaluate the fitness $f(P_i^d)$
        Replace $p_i^{best} \leftarrow P_i^d$ if $f(p_i^{best}) < f(P_i^d)$
        Replace $g^{best} \leftarrow P_i^d$ if $f(g^{best}) < f(P_i^d)$
        $d \leftarrow d + 1$
    end for
end while

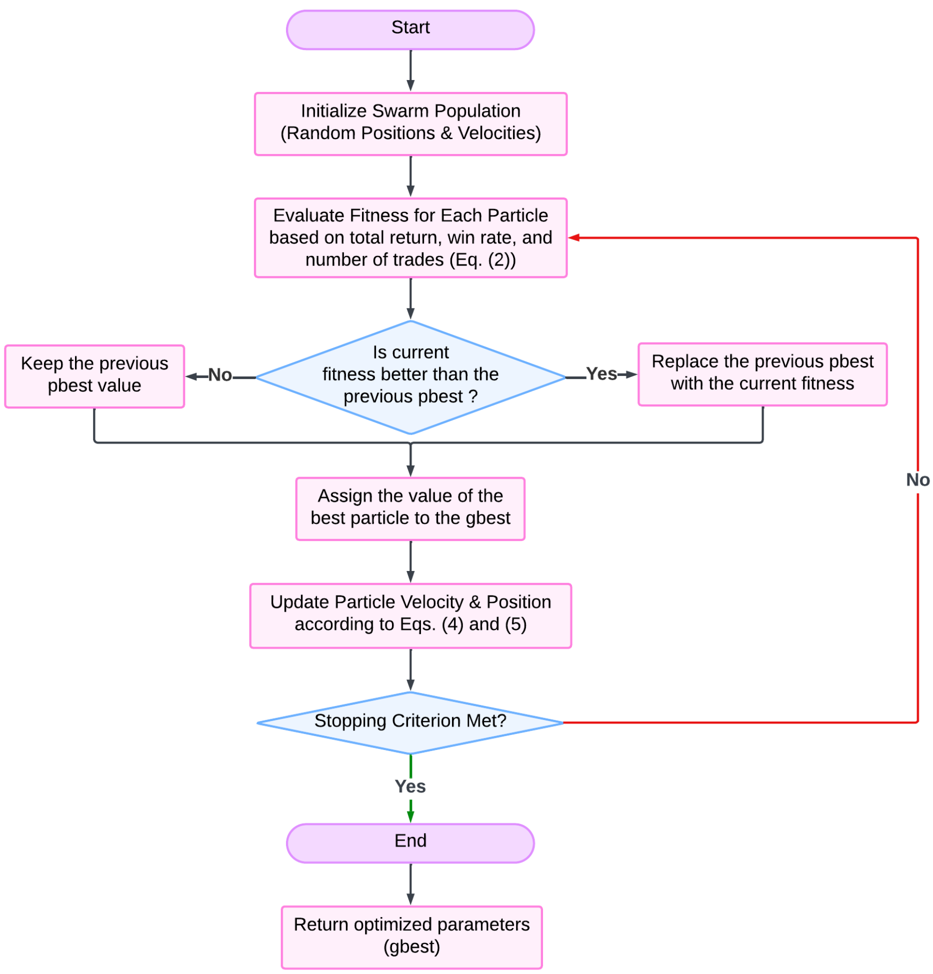

Figure 1. Flowchart for parameter optimization using PSO algorithm

The trading model in this study is based on the assumption that the investor starts with a predetermined amount of money and no additional capital is invested during the investment time frame. All profits from each trade are reinvested, so the capital is increased by winning trades and decreased by losing trades according to the amount that will be invested in subsequent trades. In addition, the system assumes that each buy signal will be followed by a sell signal and short selling is not allowed. The analysis focuses specifically on two main technical indicators: RSI and MACD.
The RSI strategy is calculated with (6):

$$RSI = 100 - \left[\frac{100}{1 + \frac{m^u}{m^d}}\right], \tag{6}$$

where m^u is the average of m-day up closes and m^d is the average of m-day down closes.

$$s_{d+1} = \begin{cases} buy & \text{if } RSI_d > b^l \\ sell & \text{if } RSI_d < b^u \end{cases}, \tag{7}$$

where s_d is the signal for day d, b^l and b^u are the lower and upper boundary, respectively.

Following [31], the typical value of m is 14 days, b^l defaults to 30 and b^u defaults to 70. In this work, each parameter of the RSI indicator is limited by the boundary constraints as follows:
- $m \in [3, 25]$
- $b^l \in [10, 40],\ b^u \in [60, 90]$

The value chosen is based on research in [32], which shows that b^l is between 10 and 40 because buy signals rarely occur when this value is below 10, b^u is between 60 and 90 in search of bigger profits. Additionally, m is chosen to be between 3 and 25 to include the typical value.
The MACD strategy is calculated with (8):

$$EMA_d^\rho(p_d) = \begin{cases} p_1 & \text{if } d = 1, \\ \frac{2}{\rho+1} \cdot p_d + (1 - \frac{2}{\rho+1}) \cdot EMA_{d-1}^\rho(p_{d-1}) & \text{if } d > 1. \end{cases} \tag{8}$$

where EMA stands for exponential moving averages, p_d refers to the current value at day d, and ρ represents the smoothing period.

Given the periods ρ, ϕ and ψ, the MACD line at day d, ($MACD_d$), is calculated by subtracting the faster EMA from the slower EMA. Then, the MACD line is used to compute the moving average of the MACD, $Signal_d$.

$$MACD_d = EMA_d^\rho(p_d) - EMA_d^\phi(p_d), \qquad Signal_d = EMA_d^\psi(MACD_d). \tag{9}$$

The trading rule is determined as (10):

$$s_{d+1} = \begin{cases} buy\& \text{ if } MACD_d > Signal_d, \\ sell\& \text{ if } MACD_d < Signal_d. \end{cases} \tag{10}$$

As stated by [2], [33], the common values of ϕ, ρ, and ψ are 26, 12, and 9, respectively. The MACD constraints are as follows:
- $\psi < \rho < \phi$
- $\psi \in [5, 10],\ \rho \in [11, 20],\ \phi \in [21, 40]$

These well-known parameters are used based on the previous study in [34].

Next, an optimal selection strategy is constructed using the optimal results from the presented technical indicators. At each period:
- MACD indicator's parameter set is optimized;
- RSI indicator's parameter set is optimized;
- Compare the results of the two indicators above to choose the best result.

Then, we define a score function that indicates the performance of the selected parameter set. Our model uses the total return, win rate, and number of trades as the evaluation metrics.

$$Total\_Return = \frac{Net\_Return}{Initial\_Investment}, \tag{11}$$

where Net_Return is the subtraction of the initial cost of the investment from its final value and the invested money is denoted as $Initial\_Investment$. This metric is typically expressed as a percentage of the amount that was invested. Win rate is calculated as the ratio of profitable trades to total trades made. The number of trades shows how many trades were placed. It starts with a buy order and ends with a sell order.

2.3. Experimental setup

The backtest system is run on historical daily data of VNINDEX, from January 1, 2018 to January 1, 2024. Some assumptions are introduced in the simulated trading environment as follows. The investment is assumed to be $1,000,000. When each trade is executed, the commission is calculated as 0.1 percent.

To avoid the overfitting problem during backtesting, we partition the dataset into training and testing periods. The time series cross-validation method will divide the dataset into 10 samples (windows), each having 375 daily observations that are considered an independent experiment (see Figure 2). The blue part is the data used to train the model, the red part is the test data. This approach aims at breaking the time series into several continuous segments where each segment is used first for the evaluation of the model and then to retrain the model. This procedure simulates reality in that models are constructed using historical information and then used to forecast future behavior. More precisely, for each series, the first 250 observations are used for estimation and the following 125 to evaluate the forecasts.

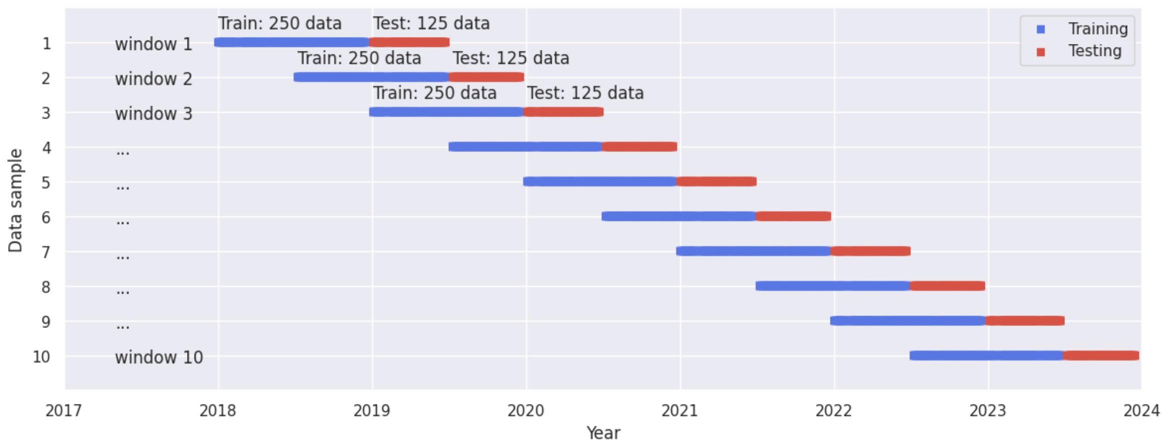

Figure 2. Time series cross-validation illustration for training and testing on VNINDEX

Multiple benchmarks are presented to test the performance of this study. First, we compare the results between the PSO method and the DE method with the same configuration of parameters. The following criteria are considered: total profit, win rate, number of trades, and execution time. Next, the performance of the optimal selection strategy and the strategy built based on the default parameter set are compared. The proposed strategy is also compared with a simple buy-and-hold (B&H) strategy.

3. RESULT AND DISCUSSION

The historical closing values of VNINDEX are shown in Figure 3. The chart shows that the index has a downward trend from 2018 to 2020, then a sharp upward trend from the second half of 2020 to early 2022, and finally, the index drops to a level close to 2018.

Figure 3. Closing value fluctuations of VNINDEX from 2018 to 2024

The PSO method and the DE method for the optimal selection strategy are compared in Table 1. PSO method achieved higher returns, higher win rates and required fewer trades than DE method. Our results indicate that the PSO method outperforms the DE method in optimizing algorithmic trading strategies over both training and testing periods. This result is consistent with the findings in [1]. The effectiveness of PSO has been proven in optimizing the technical indicators. Moreover, the PSO method beat the DE method by 1.76 times in terms of execution time. Specifically, the PSO method took 21 seconds, while the DE method took 37 seconds. These results can be applied in systems that require high-frequency optimization such as reinforcement learning transaction systems [8], [9]. Trading systems will take less time to optimize strategies and propose quick trading signals as soon as new information is received from the market.

Table 1. Comparison between different MOO approaches with the optimized strategy

Period	Approach	Avg. return (%)	Avg. win rate (%)	Avg. number of trades
Training	PSO	19.90	60.17	2.10
	DE	13.00	59.03	2.80
Testing	PSO	10.58	55.00	0.70
	DE	6.68	41.67	1.60

Next, a specific period of the backtesting results of the optimal selection strategy is shown in Figure 4. This chart consists of three parts, representing the respective changes in equity, profit/loss, and trading time. The top chart relates to the equity value. Imagine a trader started his account with $1 million, the value represents how much money he would have made or lost over time and is expressed as a percentage. The blue and yellow area at the top chart represents the period when a trader is in a drawdown phase from his previous peak equity value. The red dot represents the bottom of the worst drawdown phase he has ever experienced. In the middle chart, the size of the triangle represents the amount of the asset traded. The color of the triangle represents the profit (green) or loss (red), while the height of the triangle (Y-axis) is the size of the profit or loss, respectively. The bottom chart shows the number of trades and the time period for each trade; the color also represents the outcome of the trade, whether it was a profit with green or a loss with red. The data was considered from 03-01-2020 to 30-12-2020, including two phases: a decrease in the first 3 months and a reversal to increase sharply again in the following period.

The strategy achieved a total profit of 49.68 per cent, a win rate of 60 per cent, and a number of trades of 5. The maximum drawdown was low, -5.4 per cent in 83 days. From Table 2, the optimized MACD was chosen as the best indicator in the period. The optimized strategies could beat the default strategies, which use typical parameters since they generate better returns and win rates. They also performed a smaller number of trades among the strategies that yielded positive profits. Note that for the B&H strategy, we only compare returns because the number of trades is always equal to 1 and the win rate is always 100 per cent or -100 per cent. We can see that when the market does not have a clear uptrend, the B&H strategy does not bring high profits.

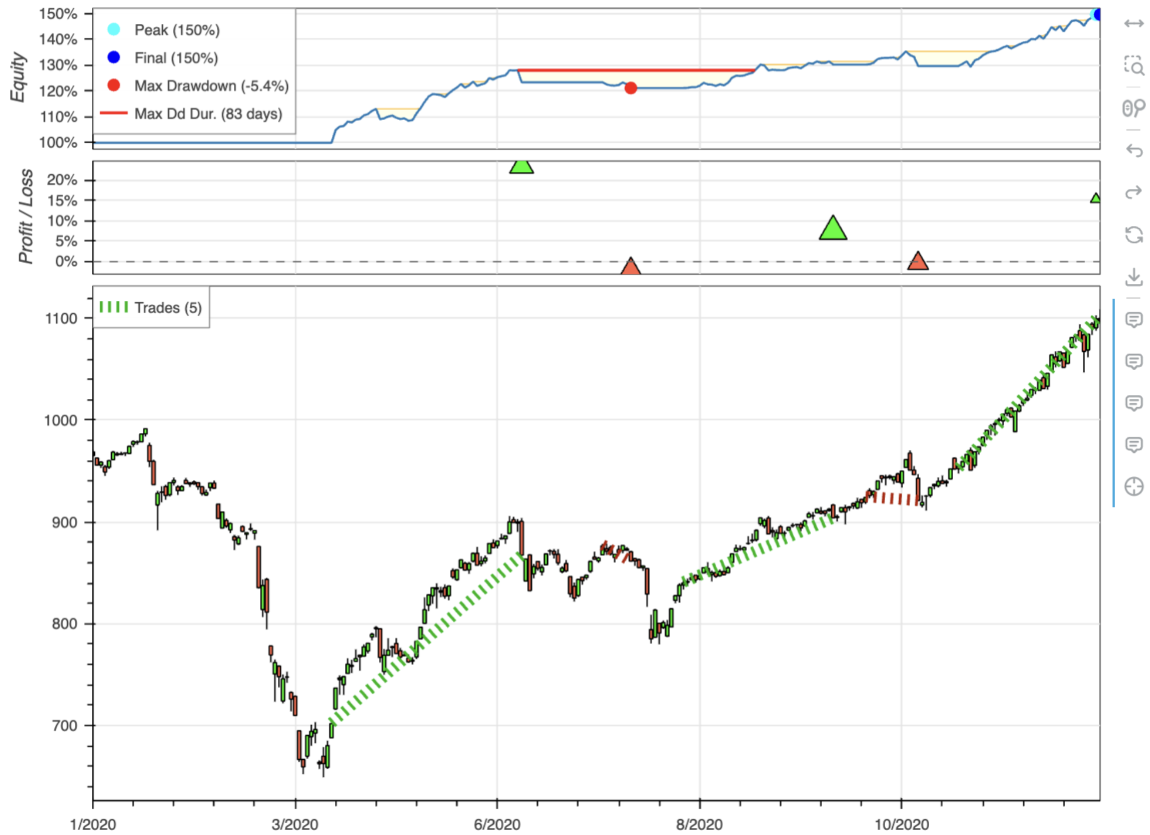

Figure 4. Backtesting results of the optimal selection strategy from 03-01-2020 to 30-12-2020

Table 2. Comparison between different strategies

Strategy	Total return (%)	Win rate (%)	Number of trades
Optimal selection	49.68	60	5
Optimized MACD	49.68	60	5
Typical MACD	47.01	50	6
Optimized RSI	24.86	100	1
Typical RSI	-1.63	50	2
B&H	13.72	100	1

Tables 3 and 4 display the performance of the studied strategies. In the training period, the optimal selection strategy achieved the highest average return of 19.90 per cent and the highest win rate of 60.17 per cent. The typical RSI strategy yielded the smallest number of trades on average; however, the average return is negative (-1.99 per cent) and the win rate is the lowest (35 per cent). In the testing period, the optimal selection strategy was also the best since it had the highest average return (10.58 per cent) and the highest win rate (55 per cent). Both optimized MACD and typical MACD could achieve positive returns in all periods, while typical RSI had negative returns.

Table 3. Performance over the training periods

Strategy	Avg. return (%)	Avg. win rate (%)	Avg. number of trades
Optimal selection	19.90	60.17	2.10
Optimized MACD	8.19	47.18	7.60
Typical MACD	6.25	43.15	8.70
Optimized RSI	2.69	40.00	0.80
Typical RSI	-1.99	35.00	1.30
B&H	4.58	100.00	1.00

Our results showed that the proposed optimal selection strategy can combine the advantages of MACD and RSI. The proposed strategy beats the single-objective optimization strategy and the default strategy in terms of average profit and win rate in both training and testing periods. The average returns of 19.90 per cent during training periods and 10.58 per cent during testing periods surpass the results of individual RSI and MACD strategies. Similarly, the win rate above 55 per cent in both periods is higher than the win rate achieved using RSI and MACD alone. These findings are consistent with results in previous studies [25]-[27]. The conclusions have shown that for different market scenarios, using only one indicator does not always give accurate buy and sell signals. Furthermore, different indicators can suggest conflicting signals. Therefore, combining multiple types of indicators is better than using single indicators. Although there is no significant difference in profits achieved, the order when combining multiple strategies is also important for traders. They need high accuracy to make the right decisions in daily trading.

Table 4. Performance over the training periods

Strategy	Avg. return (%)	Avg. win rate (%)	.number of trades
Optimal selection	10.58	55.00	0.70
Optimized MACD	4.49	52.33	3.10
Typical MACD	2.10	46.67	4.30
Optimized RSI	1.56	20.00	0.40
Typical RSI	-0.35	20.00	0.70
B&H	2.62	100.00	1.00

The number of trades from the proposed optimal selection strategy had better results when compared with the MACD strategy. It requires fewer transactions, an average of 2.1 during the training period, and an average of 0.7 during the testing period. The optimized MACD and RSI indicators have also shown a smaller number of trades compared with the default MACD and RSI indicators. These results support previous studies, which have shown profits by minimizing transaction costs [10], [35]. The fewer the transactions, the lesser the number of transactions, and hence, the lesser the transaction cost. This is an optimization algorithm that strives to balance profit with trading efficiency by combining return, win rate, and the number of trades as multiple objectives. The result will thus be a strategy that gives maximum returns, thereby minimizing the potential risks from costs.

4. CONCLUSION

This paper applies the PSO method to optimize the parameters in the automated trading system for the Vietnamese stock market. In this study, two common technical indicators, RSI and MACD, were investigated, and the optimal parameters for a multi-objective function composed of total return, win rate, and number of trades were suggested. The DE method with default parameters was used for benchmarking purposes. The results show that the two methods yield good results in backtesting with a relatively short running time, but PSO is much more efficient and effective than DE. The PSO method provides a cost-effective way to research and analyze even the most complex trading strategies and is potentially useful for a high-frequency trading system for the rapid adaptation of a strategy to new information arriving over the market.

A comparison between optimized and typical parameters reveals that optimized strategies generate higher profits with fewer trades. Specifically, the optimized MACD and RSI indicators offer distinct advantages depending on a trader's objectives. While the MACD indicator is suitable for maximizing profits, the RSI strategy becomes more effective under volatile market conditions or when transaction costs are high, helping to mitigate risks. By incorporating a multi-objective function and accounting for transaction costs, our proposed automated trading system offers a practical and comprehensive approach to parameter optimization.

Future research can expand the applicability of the PSO method by considering other markets such as derivatives, forex, and cryptocurrencies, where traders are allowed to short sell. The results of this paper also open up research directions for applying machine learning techniques to parameter optimization. Specifically, deep learning algorithms could automate the selection of technical indicators and their weightings within the MOO framework, leading to more robust trading strategies.

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Minh Tran	✓		✓	✓		✓			✓		✓		✓	✓

C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject Administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding Acquisition
Fo	: **Fo**rmal Analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

Not applicable. This study does not involve human participants or personal data.

ETHICAL APPROVAL

Not applicable. This study does not involve human participants or animals.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author Nhat M. Nguyen on request.

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