Evolving and combining technical indicators to generate trading strategies

Chawwalit Faijareon and Ohm Sornil
School of Applied Statistics, National Institute of Development Administration, Bangkok, Thailand.
E-mail: chawwalit.f@nida.ac.th

Abstract. Technical analysis is a widely used approach for trading securities. Various indicators are used, such as moving average, stochastic oscillator and relative strength index. Applications of these indicators are typically based on experiences and rules of thumb which hardly are effective in general. This paper presents a technique for evolving indicator parameters using Non-Dominated Sorting Genetic Algorithm II and combining the indicators to generate a trading strategy. Experiments are conducted using actual stocks from the Stock Exchange of Thailand show that the proposed technique generates trading strategies that outperform other well-known techniques and is applicable to real world security trading.

1. Introduction
Traditional investment instruments include trading bonds, shares, futures, options, foreign exchanges, and precious metals. Among these securities, trading stocks has been the most popular alternative. Technical analysis focuses on price and volume movements of stocks [1]. Typically, traders use indicators, such as moving average, relative strength index, moving average convergence divergence and stochastic oscillator, to determine buy and sell signals. In addition, they may use chart patterns, such as price movement patterns and candlestick chart patterns, to predict future prices and trends.

It is challenging to achieve positive gains when the market involves a large number of investors trading against each other. The efficient market hypothesis confirms that advantages gained by an investor are vulnerable to be neutralized by others when they have access to the same kind of market information [1]. Investors then try to find extra information to help in trading and consider that historical data may provide indications of future price movements.

Trading rules derived from technical analysis have become the focus of many investors, especially high-frequency traders [2]. The rules have been mostly designed with parameters adopted from general traders’ practices, such as the choices of durations in the moving average and relative strength index. Researches have begun to focus their attentions towards optimizing the trading rules. In [3-6], a genetic algorithm is employed to determine rules’ coefficients, and in [7] a multi-objective optimization algorithm is employed to determine the coefficients. Moreover, it is investigated in [8] whether adaptive rules would make the investment more profitable.

This research presents a technique to generate strategies for trading stocks where Non-dominated sorting genetic algorithm II (NSGA-II) [9] is employed to determine the best parameters for technical indicators, and a decision tree is used to combine the indicators to create a strategy. The goal is to create a trading strategy that generates a high return on investment. The experiments are conducted on
actual stock price data from Stock Exchange of Thailand, and the results are compared with other popularly used strategies.

In the rest of the paper, six technical indicators are introduced; the proposed technique is presented; results of the experimental evaluations are shown and discussed; and finally conclusions are drawn.

2. Technical indicators used in the study
Six indicators are used in this research which consist of slope, exponential moving average (EMA), moving average convergent divergent (MACD), relative strength index (RSI), stochastic oscillators (STO) and average directional index (ADX).

2.1. Slope
Slope is a linear relationship between predictor variable and dependent variable. A slope can be positive or negative and calculated as:

\[ m = \frac{(p_i - p_{i-n})}{(t_i - t_{i-n})} \]  

(1)

where \( m \) is the slope, \( p_i \) is the price at time \( t_i \). A sample trading rule based on slope is: buy if the \( n \)-day slope is positive. Parameter of this rule is \( n \) days.

2.2. Exponential moving average
Exponential moving average (EMA) is an average price in a specified period of time. The price of the last price changes and responds faster than simple moving average (SMA). It can be calculated as:

\[ EMA_t(N) = \left[ \frac{2}{n} \times (P - EMA_{t-1}(N)) \right] + EMA_{t-1}(N) \]

(2)

where \( EMA_t \) is EMA at time \( t \), \( N \) is length of EMA, \( P \) is price at time \( t \). A sample trading rule based on EMA is: buy if EMA \( N \) days is greater than price. Parameter of this EMA trading rule is \( N \) day.

2.3. Moving average convergent divergent
Moving average convergent divergent (MACD) was invented by Gerald Appel in late 1970s. It is used to track the direction of the stock and the force of the stock price by using two moving averages:

\[ MACD = EMA_{n_1} - EMA_{n_2} \]

\[ MACD Signal = EMA_{n_3 \times MACD} \]

(3)

A sample trading rule based on MACD is: buy if MACD is greater than signal. Parameters of the MACD trading rules are fast length \( n_1 \), slow length \( n_2 \), and signal length \( n_3 \).

2.4. Relative strength index
Relative strength index (RSI) is an indicator used to track the direction of a stock and measure the rate of change in stock prices over a period of time. The value is between 0 and 100 and can be calculated as:

\[ RSI = 100 \frac{100}{1 + RS} \]

(4)

where \( RS \) is the average gain of up periods during a time frame divided by average loss of down periods during the time frame.

2.5. Stochastic oscillators
Stochastic oscillators (STO) are indicators used to analyze price movements over time. STO is usually used with short-term trading. The formula is calculated as:
\[
\% K = \frac{\text{Close} - \text{Lowest Low}}{\text{Highest High} - \text{Lowest Low}} \times 100
\]
\[
\% D = n \text{ day SMA of } \% K
\]

where \text{Lowest Low} is the lowest low price in \(n\) day look back period, and \text{Highest High} is the highest high price in \(n\) day look back period. A sample trading rule based on STO is: buy if STO is greater than signal. Parameters of the STO trading rule are \(\%K_{n_1}, \%D_{n_2}\).

### 2.6. Average directional index

Average directional index (ADX) is used to determine the direction or trend of the price and can be calculated as:

\[
+DI = \frac{\text{Moving Average of } +DM}{\text{True Range}} \times 100
\]
\[
-DI = \frac{\text{Moving Average of } -DM}{\text{True Range}} \times 100
\]
\[
ADX = \text{Modify Moving Average of } \left(\frac{(+DI) - (-DI)}{(+DI) + (-DI)}\right) \times 100
\]

where \(+DM\) is the positive directional movement, \(-DM\) is the negative directional movement. A sample trading rule based on ADX is: buy if the positive directional index is greater than the negative directional index. Parameter of this trading rule is \(n\) days.

### 3. Proposed technique

In our proposed technique, for each indicator there are two trading rules associated with it. One is for buying, and the other is for selling. Parameters of each indicator are evolved by Non-dominated sorting genetic algorithm-II (NSGA-II) using 2 objective functions. Those rules are then combined by the Chi-square Automatic Interaction Detector (CHAID) algorithm to create a trading strategy. The total of 26 rules and their parameters are shown in Table 1.

| Indicators | Buy Rules | Parameters | Sell Rules | Parameters |
|------------|-----------|------------|------------|------------|
| Slope      | Price slope up in \((n1)\) days | \(n1\) | Price slope down in \((n2)\) days | \(n2\) |
| EMA        | Price more than EMA\((n3)\) | \(n3\) | Price less than EMA\((n4)\) | \(n4\) |
| EMA        | EMA\((n5)\) more than EMA\((n6)\) | \(n5, n6\) | EMA\((n7)\) less than EMA\((n8)\) | \(n7, n8\) |
| EMA        | EMA\((n9)\) slope up in \((n10)\) days | \(n9, n10\) | EMA\((n11)\) slope down in \((n12)\) days | \(n11, n12\) |
| MACD       | MACD\((n13, n14)\) more than Signal\((n15)\) | \(n13, n14, n15\) | MACD\((n16, n17)\) less than Signal\((n18)\) | \(n16, n17, n18\) |
| MACD       | MACD\((n19, n20)\) more than Threshold\((n21)\) | \(n19, n20, n21\) | MACD\((n22, n23)\) less than Threshold\((n24)\) | \(n22, n23, n24\) |
| MACD       | MACD\((n25, n26)\) slope up in \((n27)\) days | \(n25, n26, n27\) | MACD\((n28, n29)\) slope down in \((n30)\) days | \(n28, n29, n30\) |
| RSI        | RSI\((n31)\) more than Signal\((n32)\) | \(n31, n32\) | RSI\((n33)\) less than Signal\((n34)\) | \(n33, n34\) |
| RSI        | RSI\((n35)\) more than Threshold\((n36)\) | \(n35, n36\) | RSI\((n37)\) less than Threshold\((n38)\) | \(n37, n38\) |
| STO        | STO\((n39)\) more than Signal\((n40)\) | \(n39, n40\) | STO\((n41)\) less than Signal\((n42)\) | \(n41, n42\) |
| STO        | STO\((n43)\) more than Threshold\((n44)\) | \(n43, n44\) | STO\((n45)\) less than Threshold\((n46)\) | \(n45, n46\) |
| ADX        | ADX\((n47)\) slope up in \((n48)\) days | \(n47, n48\) | ADX\((n49)\) slope down in \((n50)\) days | \(n49, n50\) |
| ADX        | +DI\((n51)\) more than -DI\((n51)\) | \(n51\) | +DI\((n52)\) less than -DI\((n52)\) | \(n52\) |

### 4. Evolving trading rule parameters

In this research, the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) algorithm is used to determine the optimal parameters for the rules. NSGA-II [6] is an optimization algorithm for finding
the most likely set of possible solutions to a problem while optimizing multiple objective functions simultaneously. It can be expressed as:

\[
\text{Minimize(or Maximize)}: \{f_1(x), f_2(x), \ldots, f_m(x)\}
\]  

(7)

where \( x \) is the vector of decision variables, \( f_i(x) \) is a function of the objective \( i \), NSGA-II returns a non-dominated set of answers, called a Pareto optimal set, where any answer \( x \) is better or not dominated by another answer \( y \).

NSGA-II is an improved version of NSGA which can increase performance in the spread of solution and convergence near true-pareto optimal front. Deb K., Pratap A., Agarwal S. and Meyarivan T. [6] simulated several test problems from previous study using NSGA-II and claimed that this technique outperformed the two elitist MOEAs, i.e., PAES and SPEA. NSGA-II procedure can be described as follow:

- Create \( N \) initial, random populations.
- Calculate fitness values of each population.
- Rank the population by a non-dominated sorting.
- Calculate a Crowding Distance.
- Use a binary tournament selection, binary simulation crossover (SBX) and polynomial mutation for generating an offspring population.
- Combine parent population and offspring population.
- Rank the combined population and select \( N \) chromosomes by ranking and crowding distance for new generation.
- Check the terminating condition. If the condition is met, the last generation is assigned to the best set of solutions; else the procedure will continue by assigning the last population to the initial population.

The NSGA-II is used to determine the best parameters for trading rules. The example of chromosome encoding for MACD is shown in Table 2.

**Table 2. Chromosome encoding**

| Indicator MACD | Buy if MACD(n13, n14) more than Signal(n15) | Sell if MACD(n16, n17) less than Signal(n18) |
|----------------|-------------------------------------------|---------------------------------------------|
| n day Fast (n13) | n day Slow (n14) | n day Signal (n15) | n day Fast (n16) | n day Slow (n17) | n day Signal (n18) |

Maximum sensitivity and specificity are used as 2 fitness functions for NSGA-II in this research which can be expressed as:

\[
\text{Sensitivity_{Buy}} = \frac{TP_{Buy}}{TP_{Buy} + FN_{Buy}}
\]

\[
\text{Specificity_{Buy}} = \frac{TN_{Buy}}{TN_{Buy} + FP_{Buy}}
\]

\[
\text{Sensitivity_{Sell}} = \frac{TP_{Sell}}{TP_{Sell} + FN_{Sell}}
\]

\[
\text{Specificity_{Sell}} = \frac{TN_{Sell}}{TN_{Sell} + FP_{Sell}}
\]

\[
\text{Sensitivity} = \text{Sensitivity_{Buy}} \times \text{Sensitivity_{Sell}}
\]

\[
\text{Specificity} = \text{Specificity_{Buy}} \times \text{Specificity_{Sell}}
\]

(8)

where \( TP_{Buy} \) is the number of Buy signals from the rule while the actual tomorrow price is up, \( TP_{Sell} \) is number of Sell signals from the rule while the actual tomorrow price is down, \( TN_{Buy} \) is number of Not Buy signals from the rule while the actual tomorrow price is down, \( TN_{Sell} \) is number of Not Sell signals...
from the rule while the actual tomorrow price is Not Sell, \( FN_{\text{Buy}} \) is number of Not Buy signals from the rule while the actual tomorrow price is Not Buy, \( FN_{\text{Sell}} \) is number of Not Sell signals from the rule while the actual tomorrow price is down, \( FP_{\text{Buy}} \) is number of Buy signals from the rule while the actual tomorrow price is down, \( FP_{\text{Sell}} \) is number of Sell signals from the rule while the actual tomorrow price is up.

4.1. Creating trading strategy

The Chi-square Automatic Interaction Detector (CHAID) algorithm [10] is employed to create a trading strategy by combining rules generated from the previous step. CHAID is one of the decision tree algorithm for classification. CHAID is a multi-way tree which can split more than two nodes. The algorithm calculates independent chi-square tests to determine the p-value which is used to select the variable to separate the nodes. The statistics for the chi-square test of independence is

\[
\chi^2 = \sum_{i,j} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}
\]  

where \( i \) is 1, 2, ..., \( r \) and \( j \) is 1, 2, ..., \( c \), \( O_{ij} \) is the observed(actual) frequency value, \( E_{ij} \) is the expected frequency value. The CHAID algorithm consists of three steps, i.e., merging, splitting and stopping as follow:

- Merging step will calculate a significant test on each categorical independent variable towards the dependent variables and merge most similar categories by selecting the smallest significant or biggest p-value of the category.
- Splitting step will separate a node by considering the biggest significant or smallest p-value of independent variables obtained from the merging process.
- Stopping step will checks the creation and separation of nodes, with the following requirements:
  - If the depth of tree reaches the maximum depth limit, the data classification process stops.
  - If the size of the node is less than the minimum node size, then the node will stop splitting.

5. Experimental evaluations

To evaluate the proposed method, data of 12 stocks from Stock Exchange of Thailand (SET) during 2008 to 2017 are used in the experiments. The data are divided into training data (from 2008 to 2015) and testing data (from 2016 to 2017). Amibroker software [11] is used for backtesting and measuring effectiveness of each strategy. The proposed method is compared with 8 popular trading strategies which are:

- Buy and Hold
- EMA: if EMA(5) crossover EMA(20) then buy. If EMA(20) crossover EMA(5) then sell.
- MACD(1): if Fast(12) crossover Slow(26) then buy. If Slow(26) crossover Fast(12) then sell.
- MACD(2): if MACD(12,26) crossover Signal(9) then buy. If Signal(9) crossover MACD(12,26) then sell.
- RSI: RSI(14) less than 30 then buy. If RSI(14) more than 70 then sell.
- STO(1): if Fast(14) crossover Slow(3) then buy. If Slow(3) crossover Fast(14) then sell.
- STO(2): if Slow(14,3) more than 20 then buy. If Slow(14,3) less than 80 then sell.
- ADX: if +DI crossover -DI then buy. If -DI crossover -DI then sell.

![Table 3. Results of backtesting](image)

| STOCK  | METHOD          | Net Profit | Max. System Drawdown |
|--------|-----------------|------------|----------------------|
| ADVANC | Propose Method  | 45.37%     | -19.91%              |
|        | Buy and Hold    | 33.57%     | -25.26%              |
|        | EMA             | 20.68%     | -22.86%              |
|        | MACD(1)         | -4.88%     | -25.04%              |

| STOCK  | METHOD          | Net Profit | Max. System Drawdown |
|--------|-----------------|------------|----------------------|
| ITD    | Propose Method  | -19.49%    | -29.59%              |
|        | Buy and Hold    | -44.62%    | -50.71%              |
|        | EMA             | -19.41%    | -25.94%              |
|        | MACD(1)         | -12.71%    | -20.23%              |
The results of testing with data of 12 stocks for 2 most recent years (2016 to 2017) are shown in Table 3. Net Profit is the net profit achieved after completing all trades in the period, and Max System Drawdown is the largest peak to valley percentage decline experienced while trading in the period. We can see that strategies generated from the proposed technique yield the highest returns or are ranked among the top strategies for stocks that are in an upward trend. Also the generated strategies suffer the lowest losses or are among the top strategies for stocks that are in a downward trend. For some stocks, there may be a very few strategies that yield higher returns than our strategies; but there is no common strategy that generally outperforms our technique.

Overall, strategies generated from the proposed technique outperform 8 other comparative techniques which mean that our technique is applicable to trading actual stocks.
6. Conclusion
This paper presents a technique to generate effective trading strategies using a combination of a multi-objective genetic algorithm and a decision tree. A strategy uses rules from 6 popularly used technical indicators which are slope, exponential moving average, moving average convergence divergence, relative strength index, stochastic oscillator and directional index. Appropriate parameters for each rule are determined by NSGA-II with sensitivity and specificity used as two objective functions. A trading strategy is then created by combining the evolved rules together via the CHAID algorithm. The technique is compared with eight popularly used strategies on 12 random stocks from Stock Exchange of Thailand. The results show that the proposed technique generates trading strategies that outperform other strategies, and the technique is applicable to real-world security trading.

References
[1] Lee C I, Pan M S and Liu Y A 2001 On market efficiency of Asian foreign exchange rates: evidence from a joint variance ratio test and technical trading rules Journal of International Financial Markets, Institutions and Money 11 199-214.
[2] Fyfe C, Marney J P and Tarbert H F E 1999 Technical analysis versus market efficiency - a genetic programming approach Applied Financial Economics 9 183–191.
[3] Chen J S 2005 Trading Strategy Generation Using Genetic Algorithms Asian Journal of Information Technology 4(4) 310-322.
[4] Kwok N M, Fang G and Ha Q P 2009 Moving Average-Based Stock Trading Rules from Particle Swarm Optimization 2009 International Conference on Artificial Intelligence and Computational Intelligence.
[5] Kraithong R and Sornil O 2014 A Cooperative Coevolution Genetic Algorithm for Generating Security Trading Strategies International Journal of Applied Engineering Research 9 17859-17869.
[6] Simões A, Neves R F and Horta N 2010 An Innovative GA Optimized Investment Strategy based on a New Technical Indicator using Multiple MAS International Conference on Evolutionary Computation.
[7] Fayek M B, El-Boghdadi H M and Omran S M 2013 Multi-objective Optimization of Technical Stock Market Indicators using GAs International Journal of Computer Applications 68 41-48.
[8] Ellis C A and Parbery S A 2005 Is smarter better? a comparison of adaptive, and simple moving average trading strategies Research in International Business and Finance 19 399-411.
[9] Deb K, Pratap A, Agarwal S and Meyarivan T 2002 A fast and elitist multiobjective genetic algorithm: NSGA-II IEEE Transactions on Evolutionary Computation 6 182-197.
[10] Kass G V 1980 An Exploratory Technique for Investigating Large Quantities of Categorical Data Applied Statistics 29 119-127.
[11] Bandy H B 2012 Introduction to AmiBroker (2nd ed.) South Dakota (Blue Owl Press, Inc.)