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Evolving and combining technical indicators to generate trading strategies

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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:

$$m = \frac{(p_i - p_{i-n})}{(t_i - t_{i-n})} \tag{1}$$

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:

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

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 1970's. It is used to track the direction of the stock and the force of the stock price by using two moving averages:

$$\begin{aligned} MACD &= EMA_{n_1} - EMA_{n_2} \\ MACD\ Signal &= EMA_{n_3}\ of\ MACD \end{aligned} \tag{3}$$

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:

$$RSI = 100 - \frac{100}{1 + RS} \tag{4}$$

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:

$$\%K = \frac{Close_t - Lowest\ Low}{Highest\ High - Lowest\ Low} \times 100$$
$$\%D = n\ day\ SMA\ of\ \%K \tag{5}$$

where *Lowest Low* is the lowest low price in *n* day look back period, and *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:

$$+DI = \frac{Moving\ Average\ of\ +DM}{True\ Range} \times 100$$
$$-DI = \frac{Moving\ Average\ of\ -DM}{True\ Range} \times 100 \tag{6}$$
$$ADX = Modify\ Moving\ Average\ of\ \left(\frac{(+DI)-(-DI)}{(+DI)+(-DI)}\right) \times 100$$

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.

Table 1. Trading rules

Indicators	Buy Rules	Parameters	Sell Rules	Parameters
Slope	Prince slope up in (n1) days	n1	Prince 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:

$$Minimize(or\ Maximize):\{f_1(x), f_2(x), ..., f_m(x)\} \tag{7}$$

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:

$$\begin{aligned}
Sensitivity_{Buy} &= \frac{TP_{Buy}}{TP_{Buy}+FN_{Buy}} \\
Specificity_{Buy} &= \frac{TN_{Buy}}{TN_{Buy}+FP_{Buy}} \\
Sensitivity_{Sell} &= \frac{TP_{Sell}}{TP_{Sell}+FN_{Sell}} \\
Specificity_{Sell} &= \frac{TN_{Sell}}{TN_{Sell}+FP_{Sell}} \\
Sensitivity &= Sensitivity_{Buy} \times Sensitivity_{Sell} \\
Specificity &= Specificity_{Buy} \times Specificity_{Sell}
\end{aligned} \tag{8}$$

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_{Buy} is number of Not Buy signals from the rule while the actual tomorrow price is Not Buy, FN_{Sell} is number of Not Sell signals from the rule while the actual tomorrow price is down, FP_{Buy} is number of Buy signals from the rule while the actual tomorrow price is down, FP_{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

$$\chi^2 = \sum_{i,j} \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \tag{9}$$

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

STOCK	METHOD	Net Profit	Max. System Drawdown	STOCK	METHOD	Net Profit	Max. System Drawdown
ADVANC	Propose Method	**45.37%**	-19.93%	ITD	Propose Method	-19.49%	-29.59%
	Buy and Hold	33.57%	-25.26%		Buy and Hold	-44.62%	-50.71%
	EMA	20.68%	-22.86%		EMA	-19.41%	-25.94%
	MACD(1)	-4.88%	-25.04%		MACD(1)	-12.71%	**-20.23%**

	MACD(2)	28.14%	-23.73%		MACD(2)	-20.83%	-33.58%
	RSI	25.78%	-14.46%		RSI	-16.80%	-43.82%
	STO(1)	32.10%	**-11.79%**		STO(1)	**-4.65%**	-24.41%
	STO(2)	15.66%	-17.55%		STO(2)	-29.80%	-38.06%
	ADX	18.76%	-18.60%		ADX	-28.78%	-33.30%
AMARIN	Propose Method	2.29%	**-23.09%**	PTT	Propose Method	52.22%	-11.20%
	Buy and Hold	-16.36%	-46.00%		Buy and Hold	**84.87%**	-16.81%
	EMA	-14.15%	-30.14%		EMA	53.08%	-12.68%
	MACD(1)	-17.69%	-33.72%		MACD(1)	45.59%	-16.31%
	MACD(2)	-21.21%	-36.65%		MACD(2)	27.97%	-15.07%
	RSI	-8.38%	-36.29%		RSI	22.47%	**-8.40%**
	STO(1)	**10.96%**	-24.35%		STO(1)	26.22%	-13.61%
	STO(2)	-16.53%	-43.39%		STO(2)	16.41%	-9.17%
	ADX	-4.73%	-34.76%		ADX	65.19%	-12.24%
BBL	Propose Method	**54.87%**	-6.29%	SCC	Propose Method	8.57%	-21.56%
	Buy and Hold	34.67%	-15.79%		Buy and Hold	7.56%	-15.33%
	EMA	14.96%	-14.59%		EMA	-4.29%	-12.50%
	MACD(1)	25.57%	-14.58%		MACD(1)	-2.36%	-10.16%
	MACD(2)	-6.54%	-25.32%		MACD(2)	-9.24%	-23.77%
	RSI	7.19%	**-6.12%**		RSI	6.26%	**-8.20%**
	STO(1)	6.78%	-10.31%		STO(1)	2.09%	-17.57%
	STO(2)	4.49%	-12.68%		STO(2)	**22.56%**	-9.34%
	ADX	4.63%	-23.45%		ADX	-1.01%	-11.82%
BKI	Propose Method	**4.22%**	-6.62%	TDEX	Propose Method	**39.54%**	**-4.88%**
	Buy and Hold	0.85%	-7.40%		Buy and Hold	37.88%	-8.44%
	EMA	-4.73%	-7.89%		EMA	17.16%	-11.84%
	MACD(1)	-0.77%	-5.70%		MACD(1)	22.45%	-10.87%
	MACD(2)	-6.22%	-8.29%		MACD(2)	28.29%	-8.08%
	RSI	2.59%	**-3.43%**		RSI	16.71%	-6.25%
	STO(1)	-8.34%	-9.42%		STO(1)	30.69%	-6.45%
	STO(2)	-4.18%	-7.63%		STO(2)	6.75%	-6.45%
	ADX	-3.26%	-4.61%		ADX	21.56%	-8.04%
CK	Propose Method	1.69%	**-15.29%**	SCG	Propose Method	**81.30%**	-4.31%
	Buy and Hold	-5.36%	-25.55%		Buy and Hold	-3.20%	-13.27%
	EMA	-5.06%	-23.34%		EMA	-29.58%	-36.35%
	MACD(1)	-7.56%	-29.37%		MACD(1)	-15.63%	-19.91%
	MACD(2)	-13.63%	-29.66%		MACD(2)	-18.29%	-27.20%
	RSI	**13.86%**	-15.75%		RSI	0.00%	**0.00%**
	STO(1)	-15.05%	-25.53%		STO(1)	-4.30%	-28.00%
	STO(2)	-6.39%	-18.71%		STO(2)	-0.63%	-11.34%
	ADX	-2.01%	-24.23%		ADX	-14.35%	-18.52%
CPF	Propose Method	32.59%	**-15.26%**	VNG	Propose Method	**23.85%**	**-19.84%**
	Buy and Hold	**36.36%**	-29.02%		Buy and Hold	-20.29%	-40.11%
	EMA	-0.44%	-24.65%		EMA	-5.96%	-26.82%
	MACD(1)	11.33%	-29.80%		MACD(1)	-9.92%	-28.82%
	MACD(2)	-1.41%	-25.69%		MACD(2)	2.72%	-26.89%
	RSI	-4.50%	-21.98%		RSI	22.53%	-17.04%
	STO(1)	0.72%	-26.91%		STO(1)	-3.82%	-32.35%
	STO(2)	-7.29%	-23.54%		STO(2)	-8.61%	-30.16%
	ADX	-1.54%	-23.65%		ADX	-7.01%	-28.10%

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.

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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.

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