LARG: Loss Avoidance Technical Trading Rules using Genetic Algorithm

Suriya Yodphet, Sunisa Rimcharoen, Nutthanon Leelathakul
Faculty of Informatics, Burapha University, Thailan
suriya@oanut.com, rsunisa@buu.ac.th, nutthanon@buu.ac.th

***Abstract*—This paper proposes a genetic algorithm (GA) to find profitable stock-trading rules. In [1], the authors proposed the evolutionary algorithm, which potentially generated rules without concerning unlimited loss. We proposed two modifications to the chromosome encoding. The first one is to incorporate an exit signal (i.e., a signal for trade termination so that new rules could be generated and used for future trades) in the rules to avoid loss and increase profitability. The second is to add two more effective indicators: relative strength index (RSI, measuring price momentum) and average directional index (ADX, measuring price trend). The evolved trading rules are tested by simulating stock trades using the SET High Dividend 30 Index (SETHD) historical data from January 2015 to June 2015. The results demonstrate that the proposed method yields more practical buying/selling signals with less loss both for bullish and bearish stocks than the one of MACD and of Hybrid (μ+λ) Evolutionary Algorithm [1].**

Keywords-trading rule; genetic algorithm; stop loss; stock exchange of Thailand

I. INTRODUCTION

In 2014, the number of domestic trading accounts increases more than one million [2]. Although investing in the stock market yields a high rate of return, it comes with high risk. To overcome the market, investors need to carefully decide to buy or sell stocks. One common method that has been widely used by most investors is to monitor technical indicators. These indicators capture trends, and suggest buy/sell signals. However, if incorrectly chosen, indicators may not be able to contribute profitable signals.

The key to successful algorithmic trading is to choose and fine-tune the right indicators that could lead investors to correct decisions. Some indicators require only one parameter to be calibrated, while some may require more. Improper parameter tuning might cause unexpected loss. In some cases, using more than one indicators could suggest more lucrative buy/sell signals with more confidence before executions. In addition to many underlying uncertainties just mentioned, investors often take into account a wide varieties of chart patterns (such as Double Top Reversal and Triple Bottom Reversal) before making buy/sell decisions. The varieties of indicators (together with their parameter(s)) and chart patterns just mentioned attract many researchers to find best trading rules.

From previous research works, many researchers generally use machine learning techniques to generate trading rules. Y-H Chou, et al. [3] proposed the method that uses the quantum-inspired Tabu search algorithm to find the optimal composition and combination of trading strategies. I. Yeh and C-H. Lien [4] proposed fuzzy rule-based stock trading system for Taiwan's stock market. Ming Zhu and Lipo Wang [5] used a feed-forward multi-layer perceptron and a support vector regression to develop a predictive trading system for Hong Kong stock market. Weights of each node in these models are optimized by a genetic algorithm. N. M. Kwok et al. [6] proposed using a particle swarm optimization algorithm to determine parameters of a moving average-based stock trading rules. Qinghua Huang et al. [7] proposed using a clustering method to discover an effective combination of technical trading indicators.

All of mentioned previous works used machine learning techniques to optimize the well-known existing rules in the way of combining rules or optimizing parameters. On the contrary, some researchers attempts to achieve the goal using an alternative method. They use evolutionary computation to find new rules. It offers a variety of rules that may beyond human mind. For example, F. Allen and R. Karjalainen [8] used a genetic algorithm to find technical trading rules, while [9-12] generated trading rules by genetic programming. Y. Chen et al. [13] used genetic network programming, and S. Rimcharoen et al. [1] used a hybrid algorithm of genetic algorithm and evolution strategies to generate trading rules. The research works, above mentioned, presented only buy and sell rules. Although some of them works consider loss, they propose a stop-loss rule by simply fixing rate.

The aim of this paper is to propose using a GA to generate trading rules, which also include more sophisticated stop-loss rules. The stop-loss rules help increasing the efficiency and flexibility of trading strategies, providing more profitable strategies in both regular and very fluctuate market conditions.

II. BACKGROUND

A. Technical Indicators

Generally, there are two main approaches that investors and traders use as a guideline to trade a stock which are fundamental analysis and technical analysis. Fundamental analysis is an approach that considering basis information of the company such as revenue, asset, etc. The technical analysis determines stock trends by investigating historical prices or chart patterns. It might use various indicators, each of which

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measure different price characteristics. Although indicators require different calculation methods, they all take into account the prices during the previous *n* days. For example, the formula of a simple moving average (SMA) is shown in eq. 1, where P_{n-i} denotes the price of previous *n-i* days.

$$SMA(n) = \frac{\sum_{i=0}^{n-1} P_{(n-i)}}{n} \qquad (1)$$

Generally, traders use typical values to calculate the values of technical indicators. For example, in the above equation, {5, 10, 20, 50, 100} are widely used. Our proposed GA searches in a larger space (staring from 5 to 50), making possible better fitted parameter values.

B. *Stop loss*

Investors should incorporate Stop-loss when designing trading strategies [2]. The technique helps specifying the exit point where a short-term profit could be secured; thus, reducing the loss impact especially in severe fluctuating conditions.

This paper proposes rules that leverage Equity stop. (Investors execute Equity stop when the price falls down to a certain percentage of the cost.) A sell and exit signals are triggered when a stock price goes down to an appropriate percentage of the cost, which is derived from the proposed GA.

C. *Genetic Algorithms*

Genetic Algorithm (GA) uses the principles of evolution theory of Charles Darwin to discovery solutions, hard to determine by using other traditional methods. The algorithm imitates natural evolution principle, where stronger lives (or fitter) are more likely to survive.

GA, in general, begins with a randomly generated population. Each instance in a population is assigned a fitness value. The fitness values is used to select which instances to be parents that would generate offspring for the next generation. Crossover and mutation are two mechanisms to generate the offspring divergent from their parents. The process is then repeated until the new generation achieves the desirable fitness value.

III. APPLYING THE GENETIC ALGORITHM

This paper proposes the modification to an existing technique [1] to improve trading strategies. We add exit rules and use stop loss percentage generated by the proposed GA to secure profitability. From the literatures, many researchers have used GAs to find trading strategies. They showed that the algorithms can search for solutions efficiently. Yet, there is still a room to improve as previous methods has generated rules with fixed stop-loss percentage at most. However, variable stop-loss percentage could lead to a more prudent and careful investment.

The rule-generating process in this paper starts from randomly generating candidates and evaluating them according to a designed objective function, which embraces the percentage of stop loss to generate sell and exit rules. Then, we select candidates for the next generation. The evolution process repeats until it reaches the specified number of generations. The detailed process is as follows:

A. *Chromosome Encoding (rule's structure)*

A chromosome consists of 3 rules: buy, sell and exit rules whose structures are a binary tree. (The rules do not specify the amount of buying or selling. We leave it up to traders to decide.)

Internal nodes contain either a Boolean operator (& or |), or a comparison operator (=, <, >, <=, >=). The value of a terminal node is the value either of technical indicator, or of a constant parameter. The indicators used in this paper are simple moving average (SMA), exponential moving average (EMA), standard deviation (SD), maximum value (MAX), minimum value (MIN), average directional index (ADX), and relative strength index (RSI). Each indicator has one parameter, which is the number of previous days randomly selected by the proposed GA. The parameter's value is in the range of 5 to 50, as an indicator for short-term trading. For example, RSI(14) denotes a relative strength index of 14 days ago. The example of chromosome encoding is shown in Fig. 1.

Buy rule:
{ EMA(5) > MIN(10) } & { RSI(14) < EMA (20) }

&	EMA	5	>	MIN	10	RSI	14	<	EMA	20

Sell rule:
{ MAX(7) > SMA(15) } & { EMA(8) < SMA(16) }

&	MAX	7	>	SMA	15	EMA	8	<	SMA	16

Exit rule:
{ RSI(7) = MAX(9) } \| { ADX(20) < EMA(50) }

|	RSI	7	=	MAX	9	ADX	20	<	EMA	50

Figure 1. Example of chromosome encoding

After randomly selecting values in all nodes, rules in Fig. 1 are generated. To incorporate stop-loss percentage into a sell rule, we extend the sell and exit rules in Fig. 1 by pushing the node with value | (OR) at the root of sell and exit rules. (The sell and exit rules from Fig. 1 are now the left subtrees of the associated root.) Then, the algorithm randomly generates the percentage of stop loss in sell and exit rules, whose value ranges from 0.001% to 1%, and from 5% to 50%, respectively.

Finally, the sell and exit rules are as follows:

Sell rule:
{(MAX(7) > SMA(15) & (EMA(8) < SMA(16)} | {%Loss > 0.88}

%Loss in a sell rule is calculated each day by using the following formula: %Loss = (1 – current close price / previous open price) × 100.

Exit rule:
{(RSI(7) = MAX(9) | (ADX(20) < EMA(50)} | {%Loss > 11.876%}

To avoid possible losses in short-term investments, %Loss in an exit rule is calculated each day by using the following formula: % Loss = (total cost – current sell) / total cost × 100.

B. Fitness Evaluation

We evaluate evolved rules by executing buy, sell and exit on SET historical data. When there are buying signals, we purchase stocks at the open price on the next day. When there is still a buying signal, we will buy again only if the current price is less than the previous buying price. Later, when there is a sell or exit signals, we will sell all stocks, and calculate the profit return as follows: Profit = (selling price – avg. buying price) / avg. buying price × 100.

If there are chances to trade several times. The fitness of each candidate solution is the total sum of the percentage of profits or losses obtained during the trading period.

IV. Experiments and Discussions

The rules derived from the method described in Section III are applied to the historical data of the Stock Exchange of Thailand (SET), detailed in Table I. The trading data of each stock in SET50 and SETHD include 1) the open and close price, and 2) the highest and lowest prices during the day. Currently, there are three indexes in Stock Exchange of Thailand: SET50, SET100 and SETHD. The SET High Dividend (SETHD) 30 Index (launched on July, 2011[2]) reflects price movements of stocks that have large market capitalization, are consistently traded with high liquidity, and have constantly paid high dividend yields.

A. Performance Comparison

In this experiment, we use the same SET50 data as the ones in Hybrid EA [1]. Our proposed method generates rules incurring no loss for all stocks, as opposite to MACD and Hybrid EA. Due to space limitation, Table II shows only symbols whose average loss percentage, when Hybrid EA is applied, is more than 1. The first row shows the LARG rule that yields average profit 5.12% more than the one of Hybrid EA. The last row shows the LARG rule that yields average profit 3.85% more.

When we compare average profit of all SET50 stocks, we find that Hybrid EA's rules yield more average profit than the ones of LARG (3.94 VS 1.66). Although Hybrid EA seems to be more profitable, we argue that it is quite impractical and a risk-seeking method. Hybrid EA assumed traders has unlimited amount of money and did not avoid any loss, which is more suitable in bullish markets. In bearish markets, the traders might run out of money without a chance to make money if big loss occurs. Our proposed method, however, incurs no loss for all stocks and can survive no matter what market condition is.

TABLE I. EXPERIMENT DATA

Train Data	Test Data
SET50 10/3/12 – 5/31/13	SET50 6/3/13 – 10/30/13
SETHD 1/1/14 – 12/31/14	SETHD 1/1/15 – 6/30/15

B. LARG on SETHD

In this experiment, we use historical data of SETHD (363 days in total). The setups of our GA are the following: the population size is 100, and the searching generation is 100. We use the tournament selection strategy with size 2. The crossover and mutation rate are set to 0.8 and 0.3, respectively.

The best results from 100 runs are shown in Table III. The first column shows stocks' names (ticker symbols). The total sum of profit returns from the proposed method together with the ones of the chosen standard indicator (Moving Average Convergence/Divergence: MACD) are shown in the next three columns. The last row shows the average profit returns of all trading transactions.

The last column shows the evolved trading rules obtained from our proposed method. For instance, evolved rules for buying and selling AMATA suggest that we would buy the stocks if the standard deviation price of the previous 37 days is greater than or equal to the average directional index price of the previous 48 days, or if the simple moving average price of the previous 36 days is greater than the minimum price of the last 13 days. Then, we would sell the stocks if the maximum price of the last 27 days is less than or equal to the maximum price of the last 22 days, or if the percentage of stop loss greater than 0.586%. We should exit if the minimum price of the last 29 days is greater than the standard deviation price of the previous 42 days or if stop loss is greater than 39.429%.

The last row of Table I shows the average profit returns (%) of all stocks. It is obvious that our proposed technique, LARG, earn more profit return on average (19.53%), while MACD technique yields -2.10%. Incorporating stop-loss in sell rules and producing exit rules, LARG generates more flexible strategies, enabling trades that are more practical, while MACD and Hybrid EA produce only buy and sell signals. In addition, Stop-loss in sell rules will be able to prevent investors from severe loss.

In the experiments, the best profit return obtained from our proposed method is 58.52% (VS -19.33% of MACD), where the rules is applied to DELTA, whose price is shown in Fig. 2.

It seems that MACD outperforms LARG when the stock price slopes down quite significantly and continuously (e.g., STA's price starting from March to April 2015 in Fig. 3). The LARG rules for STA still generate profit but less than the one from MACD because the LARG rules suggest the exit too early (on 17 March). As shown in Table III, the LARG rules suggests an exit when the percentage of stop loss is greater than 5%, which happens during the down trend of consecutive days. While MACD, taking into account both short-term EMA(12) and long-term EMA(26), is less responsive to the price change: it suggests the exit in the end of June.

TABLE II. COMPARISON RESULTS

Symbol	MACD	Hybrid EA	LARG	Rules derived by LARG
KKP	-4.63	-2.11	3.01	Buy : (MIN(33) > ADX(17)) OR (ADX(28) <= SD(29)) Sell : ((MIN(49) > ADX(43)) OR (EMA(28) >= RSI(20)) OR (MIN(16) = SMA(32))) OR (%Loss > 0.9%) Exit : ((RSI(35)<EMA(23)) AND (EMA(42)>=MIN(5)) AND (RSI(14)<=EMA(17))) OR (%Loss>49.3%)
PTTGC	-0.27	-2.77	1.75	Buy : (MIN(41) <= SD(36)) AND (ADX(40) <= SD(23)) OR (EMA(50) >= SMA(10)) Sell : ((SD(25) >= MAX(48)) OR (SMA(49) > EMA(5)) OR (SD(8) >= EMA(36)) OR (SMA(15) < RSI(38)) AND (MIN(5) > SD(10))) OR (%Loss > 0.9%) Exit : ((ADX(25) > ADX(12)) AND (RSI(42) > ADX(7))) OR (%Loss > 50.0 %)
GLOW	-1.18	-1.65	2.32	Buy : (ADX(33) < MIN(27)) OR (SD(33) = MIN(32)) Sell : ((ADX(9) <= SD(23)) AND (MAX(14) > EMA(40))) OR (%Loss > 1.0%) Exit : ((EMA(44) > MAX(12)) AND (SD(30) <= MIN(44)) AND (SD(33)<=MIN(32))) OR (%Loss>28.9%)
BIGC	-2.39	-3.00	0.85	Buy : (SD(30) >= RSI(45)) OR (MAX(14) > RSI(18)) Sell : ((SD(45) > ADX(14)) OR (MAX(15) > EMA(31)) AND (MIN(13) <= SMA(27)) OR (MAX(19) >= SD(35))) OR (%Loss > 0.4%) Exit : ((SD(19) >= MIN(7)) AND (MIN(7) <= EMA(34))) OR (%Loss > 14.4%)

TABLE III. EVOLVED RULES USING LARG ON SETHD

Ticker Symbol	Profit Return %			Evolved Trading Rules
	LARG Rule		MACD	
	Train	Test		
AMATA	64.26	20.78	-3.23	Buy : (SD(37) >= ADX(48)) OR (SMA(36) > MIN(13)) Sell : (MAX(27) <= MAX(22)) OR (%Loss > 0.59%) Exit : (MIN(29) > SD(42)) OR (%Loss > 39.43%)
AP	79.59	24.65	7.25	Buy : (SMA(23) >= MIN(40)) Sell : (ADX(37)=SD(16)) AND (RSI(42)=EMA(32)) OR (SD(28)>MAX(20)) OR (%Loss>0.32%) Exit : (RSI(27) > RSI(15)) OR (MAX(48) < ADX(8)) AND (EMA(45) < MIN(32)) OR (%Loss > 36.17%)
BBL	15.77	0.81	-11.64	Buy : (ADX(5) < MIN(44)) Sell : (MAX(45) >= RSI(49)) OR (SD(50) < MIN(34)) OR (%Loss > 0.03%) Exit : (MAX(7) >= SMA(48)) OR (%Loss > 23.93%)
BCP	56.92	24.35	6.94	Buy : (EMA(23) <= MAX(21)) OR (RSI(41) <= MIN(23)) Sell : (SMA(38) <= SMA(37)) AND (SD(39) <= MIN(37)) OR (%Loss > 0.79%) Exit : (MAX(25) >= RSI(33)) OR (%Loss > 37.45%)
BECL	49.29	14.90	4.81	Buy : (MAX(36) > EMA(6)) Sell : (MAX(12) >= MIN(39)) OR (%Loss > 0.75%) Exit : (SMA(7) > RSI(38)) AND (MIN(32) >= RSI(25)) OR (%Loss > 14.24%)
DELTA	61.26	58.82	-19.33	Buy : (EMA(21) <= MAX(26)) Sell : (MAX(13) <= ADX(13)) OR (MIN(41) < EMA(40)) OR (%Loss > 0.42%) Exit : (EMA(37) >= MAX(23)) OR (%Loss > 31.09%)
EGCO	57.84	9.51	-9.89	Buy : (SMA(13) <= MAX(10)) Sell : (SD(41) < MAX(47)) OR (%Loss > 0.95%) Exit : (SMA(44) > SD(38)) AND (EMA(48) < MIN(35)) OR (%Loss > 17.80%)
GLOW	67.88	19.15	-11.10	Buy : (SMA(8) <= SMA(17)) OR (EMA(49) <= SMA(20)) Sell : (MAX(15) = SD(23)) OR (SMA(15) >= RSI(46)) OR (%Loss > 0.62%) Exit : (SD(44) <= SMA(32)) AND (ADX(14) < EMA(20)) OR (%Loss > 32.77%)
JAS	63.69	15.16	0.02	Buy : (EMA(18) > MIN(6)) Sell : (ADX(9) > EMA(26)) OR (EMA(35) <= SMA(40)) OR (%Loss > 0.76%) Exit : (SMA(48) = MIN(6)) OR (EMA(38) > SD(41)) OR (%Loss > 6.35%)
KKP	50.83	0.70	-9.74	Buy : (MAX(38) >= EMA(16)) OR (MAX(33) >= SMA(28)) OR (MAX(14) = MIN(16)) Sell : (EMA(23) <= RSI(7)) OR (RSI(40) > MAX(36)) OR (%Loss > 0.31%) Exit : (SD(38)<SMA(21)) AND (MIN(28)<MAX(37)) AND (ADX(43)<RSI(7)) OR (%Loss>40%)
KTB	62.41	10.80	-17.93	Buy : (SMA(31) < RSI(15)) Sell : (SD(42) <= MIN(15)) OR (%Loss > 0.95%) Exit : (SD(48) <= SMA(24)) AND (SMA(40) < MAX(5)) OR (%Loss > 41.93%)
LH	45.18	21.39	7.55	Buy : (MAX(13) <= RSI(8)) OR (MAX(41) >= EMA(30)) Sell : (SD(20) <= EMA(29)) OR (%Loss > 0.41%) Exit : (SD(41) <= MIN(28)) OR (%Loss > 15.62%)

TABLE III. CONTINUED

Ticker Symbol	Profit Return %			Evolved Trading Rules
	LARG Rule		MACD	
	Train	Test		
LPN	94.36	-2.19	-2.97	Buy : (RSI(20) >= EMA(29)) Sell : (SMA(37) < SD(39)) OR (%Loss > 0.98%) Exit : (SMA(20) = MIN(28)) AND (EMA(7) > ADX(41)) OR (%Loss > 5.85%)
PTT	61.08	33.84	17.44	Buy : (ADX(6) < MAX(32)) OR (SMA(42) < SD(37)) Sell : (MAX(32) >= MAX(8)) AND (EMA(49) <= MAX(15)) OR (%Loss > 0.10%) Exit : (ADX(9) <= EMA(36)) AND (ADX(27) = MAX(46)) OR (%Loss > 13.40%)
PTTEP	30.42	21.99	16.33	Buy : (SD(8) <= MAX(42)) Sell : (SMA(35) > ADX(26)) OR (%Loss > 0.20%) Exit : (EMA(11) <= MIN(17)) OR (%Loss > 14.10%)
PTTGC	30.64	33.13	13.60	Buy : (MIN(15) < EMA(49)) Sell : (MAX(48) = MIN(45)) OR (RSI(46) <= EMA(38)) OR (%Loss > 0.09%) Exit : (SMA(44) = MIN(16)) OR (MAX(37) = EMA(44)) OR (%Loss > 5.00%)
QH	78.97	14.66	8.13	Buy : (MAX(7) > ADX(28)) Sell : (EMA(40) > SMA(21)) OR (%Loss > 0.98%) Exit : (SMA(9) > SD(44)) OR (%Loss > 8.54%)
RATCH	53.93	24.63	-14.32	Buy : (MAX(46) >= EMA(18)) AND (MAX(35) >= SMA(27)) Sell : (SD(45) >= SD(36)) OR (SD(21) < EMA(16)) OR (%Loss > 0.07%) Exit : (EMA(20) < ADX(29)) AND (SMA(5) = ADX(37)) AND (RSI(29)=SMA(36)) OR (%Loss>5.01%)
SAMART	100.66	20.75	-33.65	Buy : (ADX(17) <= SMA(38)) Sell : (SD(23) < RSI(39)) OR (MIN(14) < RSI(24)) OR (%Loss > 0.48%) Exit : (MAX(17) > RSI(36)) OR (MAX(16) = SMA(33)) OR (%Loss > 39.81%)
SCB	29.84	4.48	-18.17	Buy : (EMA(39) > SMA(7)) Sell : (MAX(46) = MAX(47)) OR (MIN(47) > SMA(22)) OR (%Loss > 0.35%) Exit : (SMA(43) >= SD(38)) OR (%Loss > 32.10%)
SCC	11.46	14.81	-1.01	Buy : (EMA(30) <= SMA(25)) Sell : (MAX(13) > SMA(14)) OR (%Loss > 0.13%) Exit : (EMA(44) >= SMA(22)) OR (MAX(13) < RSI(29)) OR (%Loss > 16.70%)
SGP	53.23	43.99	-2.00	Buy : (SD(46) > EMA(31)) OR (SMA(37) <= ADX(26)) Sell : (RSI(39) > SD(43)) OR (%Loss > 0.38%) Exit : (SD(35) <= EMA(31)) OR (%Loss > 39.59%)
SIRI	44.89	31.49	22.72	Buy : (ADX(37) <= EMA(11)) OR (RSI(26) >= ADX(24)) AND (RSI(35) >= EMA(19)) Sell : (SMA(41) > EMA(50)) AND (RSI(41) > SD(36)) OR (SD(36)> RSI(21)) OR (%Loss>0.28%) Exit : (MIN(50) <= SD(8)) AND (EMA(48) = MIN(10)) AND (SD(43) >= MIN(10)) OR (%Loss > 10.21%)
SPALI	101.30	7.80	-7.88	Buy : (ADX(50) < SMA(42)) OR (MAX(20) > SMA(25)) Sell : (ADX(40) < EMA(13)) AND (SMA(19) < RSI(37)) AND (MAX(37) > ADX(42)) OR (%Loss > 0.47%) Exit : (SD(14) >= MIN(50)) OR (MIN(10) >= SD(44)) OR (%Loss > 30.40%)
STA	49.93	5.12	13.50	Buy : (EMA(48) > MIN(22)) Sell : (RSI(29) >= MAX(40)) OR (MIN(41) > EMA(16)) AND (EMA(23) <= SD(36)) OR (%Loss>0.72%) Exit : (SD(7) = RSI(31)) AND (MAX(7) < RSI(24)) OR (%Loss > 5%)
TCAP	30.67	10.25	-5.15	Buy : (MIN(12) > ADX(35)) AND (EMA(20) <= MAX(36)) Sell : (MIN(11) < RSI(25)) OR (MIN(15) >= EMA(23)) OR (%Loss > 0.24%) Exit : (SMA(19) >= SMA(37)) AND (EMA(34) > SD(46)) AND (SMA(46) > ADX(22)) OR (%Loss > 26.04%)
TICON	21.99	5.84	5.45	Buy : (SMA(39) >= MIN(13)) Sell : (EMA(17) < SMA(28)) OR (%Loss > 0.73%) Exit : (MIN(17) >= RSI(7)) OR (MAX(48) = ADX(13)) OR (%Loss > 6.24%)
TISCO	58.88	24.86	-4.81	Buy : (EMA(42) >= MIN(31)) Sell : (MAX(13) >= SMA(25)) OR (MIN(26) = EMA(46)) OR (%Loss > 0.69%) Exit : (SD(39) < MIN(34)) AND (MIN(13) >= RSI(33)) OR (%Loss > 27.80%)
TOP	27.08	38.92	3.32	Buy : (MAX(43) > MIN(26)) Sell : (EMA(47) <= MAX(33)) OR (%Loss > 0.43%) Exit : (MIN(26) > EMA(25)) OR (%Loss > 25.49%)
TUF	63.98	30.56	-17.21	Buy : (MAX(15) >= MAX(6)) Sell : (MAX(25) <= MAX(37)) OR (%Loss > 0.79%) Exit : (SD(18) >= MIN(47)) AND (SD(29) > EMA(29)) OR (%Loss > 35.77%)
Average	53.94	19.53	-2.10	

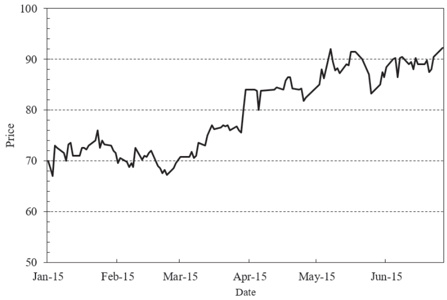

Figure 2. Stock price of DELTA

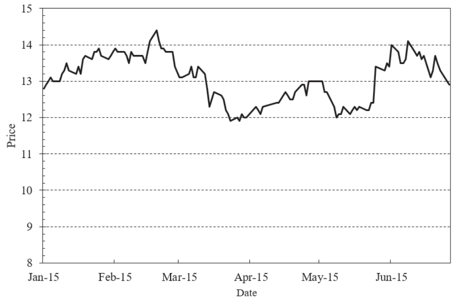

Figure 3. Stock price of STA

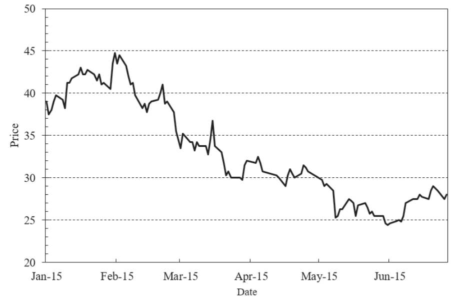

Figure 4. Stock price of SAMART

In some cases, MACD could suffer from severe loss. See Fig. 4 as an example. MACD incurs 33% loss when the price of SAMART is going up and down so rapidly that MACD cannot capture the downward trend soon enough. In the opposite, our method could make 20.75% profit.

The only one stock that LARG cannot prevent from loss is LPN. This is because LPN is obviously in the down trend. The stock price went down more than 40% within 6 months. Benefiting from the stop-loss protection, LARG incurs only 2.19% loss, still lower than MACD (-2.97%).

V. CONCLUSIONS

We propose a genetic algorithm to evolve stock trading strategies. In addition to buy and sell rules, the strategies include stop-loss percentage into sell and exit rules. The results show our propose method outperforms MACD in the trades of all stock (except STA). The highest profit return is 58.52%. The experiments also shows that the exit rule and stop loss percentage in trading strategy yield more profit. In the future, we plan to evolve more profitable rules by including more indicators, applying our evolved rules to more historical data at a longer time, and to compare the results with other commonly-used strategies. Also, we will determine more suitable methods to determine the values of stop loss percentage.

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