An Empirical Study of Genetic Programming Generated Trading Rules in Computerized Stock Trading Service System

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Abstract— **Technical analysis is aimed at devising trading rules capable of exploiting short-term fluctuations on the financial markets. The application of Genetic Programming (GP) as a means to automatically generate such trading rules on the stock markets has been studied. Computational results, based on historical pricing and transaction volume data, are reported for the thirty component stocks of the Dow Jones Industrial Average index. Statistical evidence shows that for the stocks that were studied, the use of GP based trading rules ensures a positive dollar return in all market scenarios. The performance of the GP based trading rules was also evaluated against the performance of the popularly used MACD technical indicator. In general, GP based trading rules offer greater returns over the simple buy and hold approach than the MACD trading signal.**

Index Terms—**Genetic Programming, Stock markets, Technical Analysis, Trading Rules**

I. Introduction

TRADERS try to profit from short-term price movements by active and frequent buying and selling of securities, their time horizons ranging from several seconds to several weeks. Most stock traders are firm believers and users of technical analysis [1]. Stock traders use trading rules generated by their own designed trading service systems. Critical success factors to reap the excess returns from the stock trading service system are how and when (market timing) the trading signals (buy or sell) are generated.

Investors, on the other hand, purchase stocks with the intention of holding for an extended period of time, within several months or years. Most of them believe in the buy and hold strategy. Buy and hold [2] is a passive investment strategy in which an investor buys stocks and holds them for a long period of time, regardless of the fluctuations in the market. It is based on the concept that in the long run financial markets give a good rate of return despite periods of volatility or decline. Investors perform thorough analysis in order to identify promising stocks, purchase promising stocks, and then sit back and wait.

In general, successful traders earn more profit compared to investors since they always take advantage of stock price movements by buying or selling rapidly [3, 4]. However, some unsuccessful traders often end up losing due to frequent trading because of the cumulative effect of trading costs.

As technical analysis is purely based on the identification of patterns and trends in historical price and volume data, it is suitable for computer aided trading. The generation of buy and sell signals through the application of certain technical indicators to current price and volume data can be automated.

Genetic Programming (GP) can be a useful tool for the generation of technical rules for securities trading [5]. The tree-like structure provided by Genetic Programming provides a better representation of a composite trading rule comprised of different simple rule. Given the potential for technical trading rules to be automated, we have explored the use of genetic programming to optimize such trading rules in order to earn traders greater returns.

The use of technical analysis to predict stock prices from historical price and volume patterns is based on the principle that a technical trading rule should have constant validity over time. This is accord with the primary assumption behind technical analysis, that is, in the securities markets; history tends to repeat itself due to the relative constancy of trader behavior [6]. Summers et al (2004) [7] investigated the extent to which trading rules derived entirely from a particular time period can have validity over a variety of different time periods. They found that rules derived from the data from the early period can be predictive at a later date and, often unexpectedly, can even surpass the predictive power of rules derived from more contemporary data. In our research, the same technical rule is applied to determine long or short positions in a particular stock over the entire time series being considered.

Allen and Karjalainen (1999) [8] used a genetic programming paradigm to generate technical trading rules for the S&P 500 index using daily prices from 1928 to 1995. They found that when transaction costs were considered, the rules did not earn consistent excess returns over a simple buy-and-hold strategy in the out-of-sample test periods.

Potvin *et al* (2004) [9] carried out tests to report the viability of GP based trading rules against the simple buy and hold strategy for 14 Canadian companies listed on the Toronto Stock Exchange. The results showed that the trading rules generated by GP were generally beneficial when the market fell or when it was stable. On the other hand, the GP based rules did not match the buy-and-hold approach when the market was rising. Potvin *et al's* (2004) [9] findings exclude brokerage fees that are payable for each trade carried out. Chen (2006) [10] found evidence that technical analysts can learn more about the future pattern of returns by using volume

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in conjunction with price data than those who only watch price movements, which is the strategy followed in our experiment.

This study seeks to empirically test GP generated trading rules on the component stocks of the Dow Jones Industrial Average (DJIA) to obtain evidence in supporting the technocrats' proposition that such rules can yield superior profit. In order to consider a more realistic situation and to be able to compare the returns given by our GP based trading rules against those by a simple buy and hold strategy, we incorporate the provision for brokerage commission in our fitness function. The trading return performance of such GP based trading rules in comparison with a simple buy and hold strategy was analyzed on the thirty component stocks of the DJIA index. The scope of performance measurement also includes a comparison of the returns generated by GP based trading rules against the returns generated by using the Moving Average Convergence Divergence (MACD) technical indicator over the same time series.

II. GENETIC PROGRAMMING

The Genetic Programming paradigm can be a useful tool for the generation of composite technical trading rules. It allows the evolution of programs encoded as tree structures. These programs are constructed from a predefined set of functions and terminals (which may be variables, like the state variables of a particular system, or constants, like integer 3 or boolean False). The evolution of programs within the genetic programming framework can be summarized as follows:

Step 1: *Initialization*. Create an initial random population of P programs. Set the current population to this initial population.
Step 2: *Selection*. Select P programs in the current population (with replacement). The selection process is probabilistically biased in favor of the best programs according to their fitness.
Step 3: *Modification*. Apply reproduction or crossover to the selected programs.
Step 4: *Evaluation*. Evaluate the fitness of each offspring in the new population.
Step 5: Set the current population to the new population of offspring.
Step 6: Repeat steps 2–6 for a predefined number of generations or until the system does not improve anymore.

The final result is the best program generated during the search. Details on the implementation of GP generated trading rules are given in Mallick (2008) [11].

III. USE OF MACD AS A TECHNICAL INDICATOR FOR STOCK TRADING

MACD, which stands for Moving Average Convergence / Divergence, is a technical analysis indicator created and introduced by Gerald Appel in 1979 [12]. Being a popularly used technical indicator for generating buy and sell signals, MACD can be a useful benchmark to test the performance of GP based trading rules. Comparing the returns generated by the GP [13, 14] evolved composite trading rules with the returns generated by the use of MACD as a single technical indicator will allow us to evaluate the efficacy of evolving trading rules using an evolutionary algorithm paradigm.

The most popular formula for the "standard" MACD is the difference between a security's 26-day and 12-day Exponential Moving Averages (EMAs).
MACD = EMA[12] of price – EMA[26] of price
Signal = EMA[9] of price,
where EMA[x] refers to the Exponential Moving Average for the past x periods.

The Exponential Moving Average is a weighted moving average such that recent prices have greater weight than past prices. The current period's EMA[N] is calculated by

$$EMA = (P \times \alpha) + \text{Previous EMA} \times (1 - \alpha))$$

where
P = Current Price

Smoothing Factor = $\alpha = \dfrac{2}{1+N}$

N = Number of Time Periods
Previous EMA = EMA[N] of the previous period

For the 1st period (since there is no Previous EMA available), the EMA is the simple average of the prices over the past N periods (inclusive of itself). Thus, in order to calculate MACD and Signal values, we need to obtain the price data for 26 periods prior to the starting period in addition to the regular price data spanning the different time periods that are being tested.

The trading signals generated by MACD can be summarized as follows.

MACD line crossing the signal line
BUY – Crosses up the signal line
SELL – Crosses down the signal line

MACD line crossing zero
BUY - Crosses up through zero
SELL – Crosses down through zero

IV. EXPERIMENT

A. Data Used

For the study, stocks of the thirty constituent companies of the Dow Jones Industrial Average (DJIA) were used (as listed in Table I). These companies span different industries and thus offer an opportunity to test our GP on stock data belonging to a diversified set of activity sectors. The historical data used included the stock price and the transaction volume for each working day between January 3, 2000 and December 29, 2006, for a total of 1759 days.

Table I
Constituent Stocks of the DJIA

Symbol	Company Name	Industry
AA	Alcoa	Aluminum
AIG	American International Group	Full Line Insurance
AXP	American Express	Consumer Finance
BA	Boeing	Aerospace & Defense
C	Citigroup	Banking
CAT	Caterpillar	Commercial Vehicles & Trucks
DD	DuPont	Commodity Chemicals
DIS	Walt Disney	Broadcasting & Entertainment
GE	General Electric	Diversified Industrials
GM	General Motors	Automobiles
HD	Home Depot	Home Improvement Retailers
HON*	Honeywell	Diversified Industrials
HPQ	Hewlett-Packard	Diversified Computer Systems
IBM	IBM	Computer Services
INTC	Intel	Semiconductors
JNJ	Johnson & Johnson	Pharmaceuticals
JPM	JPMorgan Chase	Banking
KO	Coca-Cola	Beverages
MCD	McDonald's	Restaurants
MMM	3M	Diversified Industrials
MO*	Altria Group	Tobacco
MRK	Merck	Pharmaceuticals
MSFT	Microsoft	Software
PFE	Pfizer	Pharmaceuticals
PG	Procter & Gamble	Non-durable Household Products
T	AT&T	Telecoms
UTX	United Technologies Corporation	Diversified Industrials
VZ	Verizon Communications	Telecoms
WMT	Wal-Mart	Broadline Retailers
XOM	ExxonMobil	Integrated Oil & Gas

* On February 19, 2008, Altria Group and Honeywell were replaced by Chevron Corporation and Bank of America in the Dow Jones Industrial Average.

B. Training and Testing Periods

The GP based trading rules were evolved on the training data. The trading rules obtained on the training period were then evaluated on previously unseen data associated with a testing period. Both long and short training periods were considered.

For each of the training periods, two possible testing period scenarios were evaluated – a short testing period and a long testing period. This was done in order to evaluate the impact (if any) of the length of the time period used for training as well as that used for testing the GP based trading rules. The exact time periods used for the experiments are reported below.

Short Training Period
January 2, 2003 to December 30, 2005 (756 periods)
Short Testing Period
January 3, 2005 to December 29, 2006 (503 periods)
Long Testing Period
January 3, 2000 to December 31, 2003 (1004 periods)

Long Training Period
January 3, 2000 to December 31, 2003 (1004 periods)
Short Testing Period
January 3, 2005 to December 29, 2006 (503 periods)
Long Testing Period
January 2, 2003 to December 30, 2005 (756 periods)

C. Parameter Settings

Preliminary experiments were performed to determine the best parameter settings for the GP. Based on these experiments, the parameter values shown in Table II were finally selected.

Table II
Parameter Settings for GP

Population Size	500
Number of Generations	50
Selection Method	Ranking based fitness proportionate
Reproduction Rate	0.35
Crossover Rate	0.60
Mutation Rate	0.05

The set of rule trees comprising 500 individuals obtained after the 50th generation is the set of GP based trading rules that is to be considered for our experiment. The best performing trading rule in this set i.e. the one which gives the maximum excess return over buy and hold for the particular stock over that time series is noted. This trading rule is then tested against unseen data (i.e. for the same stock but spanning a different time period) and the returns generated are analyzed.

V. Computational Results

A. Performance of GP based trading rules against Simple Buy and Hold

The computational tests were run on a 1.5 GHz Pentium 4 PC. The returns obtained using the best GP rule in the population in the final generation are noted. For each stock, the numbers reported are the average of 20 different runs.

The excess returns generated by the GP based trading rules over the simple buy and hold strategy are computed. The GP based trading rules are evolved over a short training period and then the same trading rules are evaluated on unseen short and long testing period data. These results are tabulated in Table III. The same experiment is repeated by evolving the GP based trading rules over a long training period and the results obtained are tabulated in Table IV.

Table III
Numerical Results for GP based rules trained on the Short Training Period

Excess Return by GP over Buy and Hold			
Symbol	**Training**	**Short Testing**	**Long Testing**
AA	19.17%	492.47%	115.85%
AIG	-44.93%	-77.14%	115.31%
AXP	-4.59%	10.73%	105.79%
BA	-49.17%	-63.79%	802.41%
C	-35.74%	-67.23%	371.56%
CAT	223.54%	157.19%	-33.96%
DD	549.21%	387.26%	106.82%
DIS	10.34%	-63.84%	263.98%
GE	-8.77%	12.11%	110.18%
GM	121.90%	136.66%	132.71%
HD	-0.74%	216.11%	152.07%
HON	-0.95%	-28.91%	160.16%
HPQ	10.47%	-21.65%	137.32%
IBM	228.31%	201.87%	203.39%
INTC	29.67%	189.20%	131.43%
JNJ	-47.68%	-94.30%	116.10%
JPM	-8.02%	-13.14%	134.26%
KO	119.28%	-80.76%	165.76%
MCD	-21.42%	-40.49%	122.76%
MMM	107.63%	124.13%	265.92%
MO	-20.29%	-57.20%	-8.75%
MRK	114.87%	-49.86%	156.52%
MSFT	102.31%	-97.42%	103.72%
PFE	110.92%	178.47%	-88.31%
PG	117.45%	-76.40%	143.09%
T	146.34%	-79.99%	116.28%
UTX	438.51%	112.54%	14.60%
VZ	125.44%	141.20%	122.51%
WMT	159.04%	100.00%	135.32%
XOM	-4.36%	-33.23%	133.23%
OVERALL			
Mean	83.32%	51.71%	151.41%
Standard Deviation	138.83%	149.88%	152.75%
Skewness	1.93	1.28	2.78
Excess Kurtosis	4.23	1.38	11.48

Table III clearly shows that on average GP based trading rules outperform the simple buy and hold strategy. Our statistical results support the application of GP based trading rules to realize profits in contrast to following a passive buy and hold strategy when trading in the stocks that constitute the DJIA.

Another point to be noted is the difference in magnitude of the positive returns against buy and hold and the negative returns against buy and hold. For the training period, if we only consider the 18 stocks for which GP based trading rules perform better than the buy and hold strategy, the mean excess return is 151.91%. On the other hand, if we only consider the 12 stocks for which GP based trading rules perform worse than the buy and hold strategy, the mean excess return is -20.56%. Similarly, for the short testing period, the mean excess return in case of stocks for which GP outperforms buy and hold is 175.71% whereas the mean excess return in case of stocks for which GP performs worse is -59.08%. For the long testing period, the mean excess return in case of stocks for which GP outperforms buy and hold is 171.82% whereas the mean excess return in case of stocks for which GP performs worse is -43.67%. Thus the average magnitude of the positive returns is far greater than the average magnitude of the negative returns. Thus GP based trading rules trained on the short training period data on average outperform the buy and hold strategy. However, for those stocks for which the buy and hold strategy gives better results than GP, the magnitude of the losses that we will incur if we use GP based trading rules is much smaller in comparison to the magnitude of the gains to be made using GP based trading rules on the remaining stocks.

From Table IV we note that when trained over the Long Training Period and then tested on two sets of testing data, the performance of the GP based trading rules against the simple buy and hold strategy is similar to the results obtained when the GP based trading rules were trained over the Short Training Period. The average magnitude of the positive returns is far greater than the average magnitude of the negative returns for the training data as well as both the sets of testing data for GP based rules trained on the Long Training Period.

Thus we can statistically infer that GP based trading rules on average outperform the buy and hold strategy. However, for those stocks for which the buy and hold strategy gives better results than GP, the magnitude of the losses that we will incur if we use GP based trading rules is much smaller in comparison to the magnitude of the gains to be made using GP based trading rules on the remaining stocks.

Table IV
Numerical Results for GP based rules trained on the Long Training Period

Excess Return by GP over Buy and Hold			
Symbol	**Training**	**Short Testing**	**Long Testing**
AA	113.25%	260.62%	-46.19%

AIG	123.90%	-82.49%	-70.12%
AXP	105.63%	-89.79%	-77.23%
BA	1470.59%	-30.38%	-36.44%
C	388.76%	-80.04%	-57.63%
CAT	-34.40%	129.05%	146.78%
DD	111.10%	122.79%	388.09%
DIS	234.01%	-52.17%	15.79%
GE	103.06%	-85.35%	-89.57%
GM	118.17%	102.93%	116.71%
HD	115.60%	102.33%	-69.89%
HON	127.46%	-92.46%	-68.22%
HPQ	111.45%	-83.06%	-71.75%
IBM	215.93%	522.36%	323.11%
INTC	115.68%	116.26%	-68.36%
JNJ	117.42%	-64.86%	-60.71%
JPM	114.83%	-89.31%	-76.97%
KO	212.17%	-89.42%	107.80%
MCD	105.80%	-87.85%	-87.97%
MMM	492.27%	194.21%	125.16%
MO	-11.65%	-59.38%	-34.93%
MRK	138.89%	-65.79%	107.76%
MSFT	104.70%	-89.92%	101.78%
PFE	248.99%	392.52%	132.36%
PG	148.18%	-99.55%	100.14%
T	120.75%	-94.90%	141.37%
UTX	-13.02%	106.37%	370.74%
VZ	122.05%	101.86%	122.14%
WMT	167.89%	107.34%	138.48%
XOM	133.54%	-78.88%	-52.39%
OVERALL			
Mean	190.06%	29.09%	49.42%
Standard Deviation	267.67%	158.93%	138.20%
Skewness	4.14	1.56	1.06
Kurtosis	19.31	2.25	0.46

From both Table III and IV, it is noted that the excess return given by GP based trading rules over buy and hold is positively skewed for the training data as well as for both the sets of testing data. We must also note that the excess return given by GP based trading rules for the component stocks of the DJIA forms a leptokurtic distribution, i.e. a distribution with a positive excess kurtosis, for the training data as well as for both the sets of testing data [15].. Thus we find that the mean excess return given by GP based trading rules for all the thirty stocks in consideration is not truly reflective of the excess return given by GP based trading rules for an individual stock. This is expected as the GP based trading rule for each stock is different. The trading rule used for a particular stock is evolved through training on the price and volume data of the individual stock and not the index as a whole.

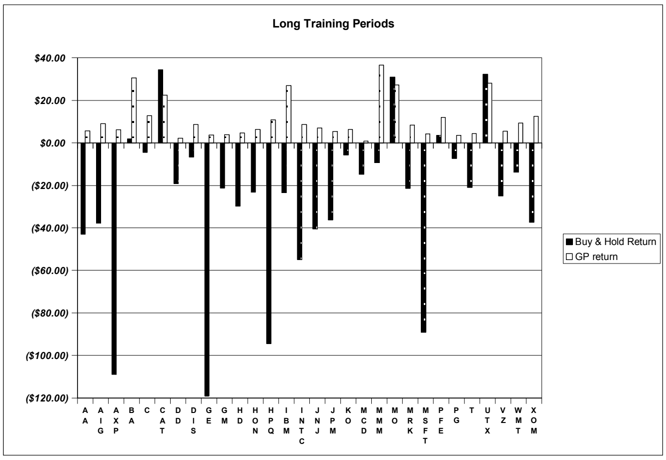

Fig. 1. Buy & Hold Return vs. GP Return for Long Training Periods

Fig. 1 compares the dollar value of the return generated by the GP based trading rules against the dollar value of the return generated by the simple buy and hold strategy in case of GP based trading rules trained on the Long Training Period.

We observe that the dollar return generated by the GP based trading rules (trained over the long training period) is positive for all the component stocks of the Dow Jones Industrial Average. Hence, statistically we can interpret these results to suggest that a trader who will make use of these GP based trading rules will be ensured of a profit (taking in account all brokerage commissions that are paid) when he invests in any of the component stocks of the DJIA.

Similar results are observed for both GP based trading rules trained on the Short Training Period and those trained on the Long Training Period under the different possible training and testing time series in consideration.

Statistically, we can effectively conclude that our GP based trading rules outperform the buy and hold approach in case of falling markets. In case of rising markets, the performance of the GP based trading rules as compared to buy and hold cannot be accurately predicted. However, our statistical results confirm that in all market scenarios (whether rising or falling), the GP based trading rules would generate a positive return for the trader.

B. Comparison with MACD

The excess returns over buy and hold generated by the GP based trading rules is compared against the excess returns over buy and hold generated by using the MACD technical trading rule to generate buy and sell signals. Fig. 2 graphically shows the excess return over buy and hold generated by GP based trading rules trained over the Long Training Period compared against the excess return over buy and hold generated by the MACD trading signal. Similar results are observed for both GP based trading rules trained on the Short Training Period and those trained on the Long Training Period under the different possible training and testing time series in consideration.

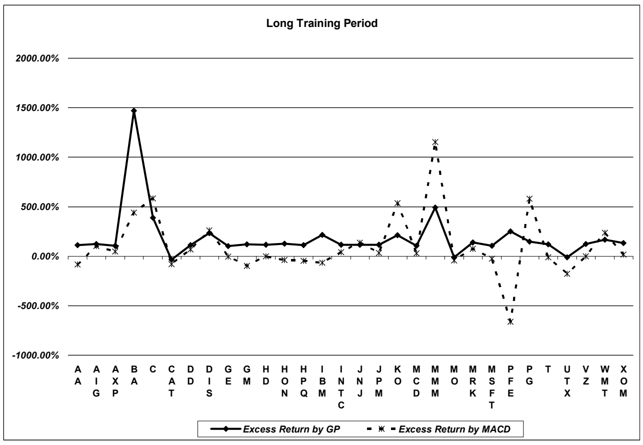

Fig. 2 – Excess returns obtain from GP and MACD generated trading rules

For all the time series that we examined, we find that the GP based trading rules perform better than the MACD trading signal for more than 75% of the stocks that the experiment is being carried out on. Hence, the statistical inference is that using composite trading rules that have been evolved on historical price and volume data using a genetic programming paradigm will generally give us better returns compared to using the MACD technical trading signal for identifying bullish and bearish trends in the market.

VI. CONCLUSION

The performance of GP based trading rules was evaluated on the 30 component stocks of the Dow Jones Industrial Average index which comprises stocks listed on the New York Stock Exchange and the NASDAQ.

Statistical evidence supported the hypothesis that GP based trading rules outperform the buy and hold approach in case of falling markets. In case of rising markets, the performance of the GP based trading rules as compared to buy and hold cannot be accurately predicted. However, our statistical results confirm that the GP based trading rules generate a positive return for the trader under all market conditions (whether rising or falling). It was also noted from the statistical results that the use of GP based trading rules ensured an excess return of at least 100% over the simple buy and hold strategy in cases when the buy and hold return is negative, thus ensuring a positive dollar return for the trader.

It was also found that in general, GP based trading rules offer greater returns over the simple buy and hold approach than the MACD trading signal. These statistical results also emphasize that the use of composite trading rules that have been trained and evolved over relevant stock data is more beneficial than the use of a single technical indicator to identify bearish and bullish trends in the stock market.

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