Stock Market Timing Using Artificial Neural Networks and Genetic Algorithms

Verification of Results By Monte Carlo Testing

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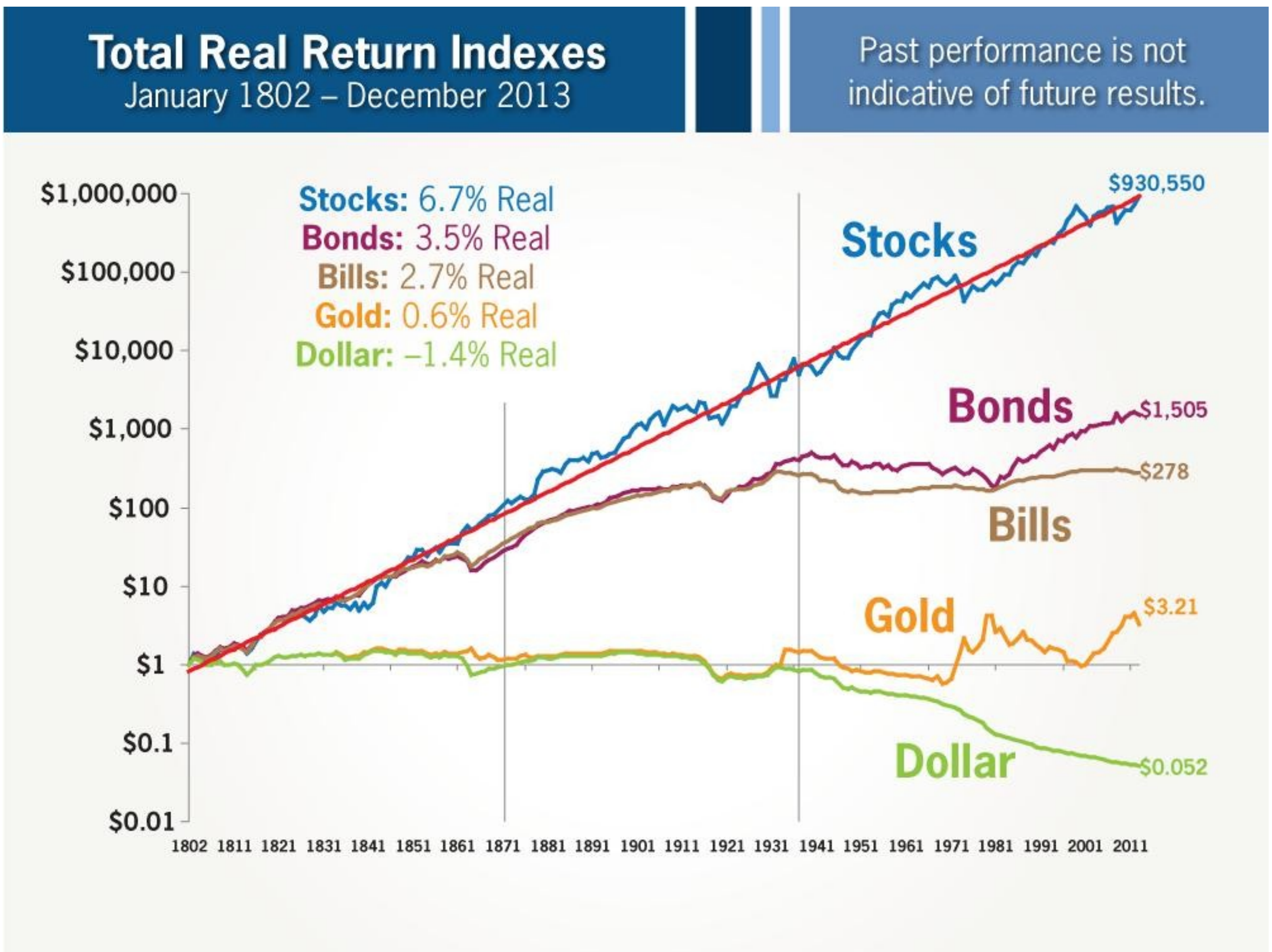
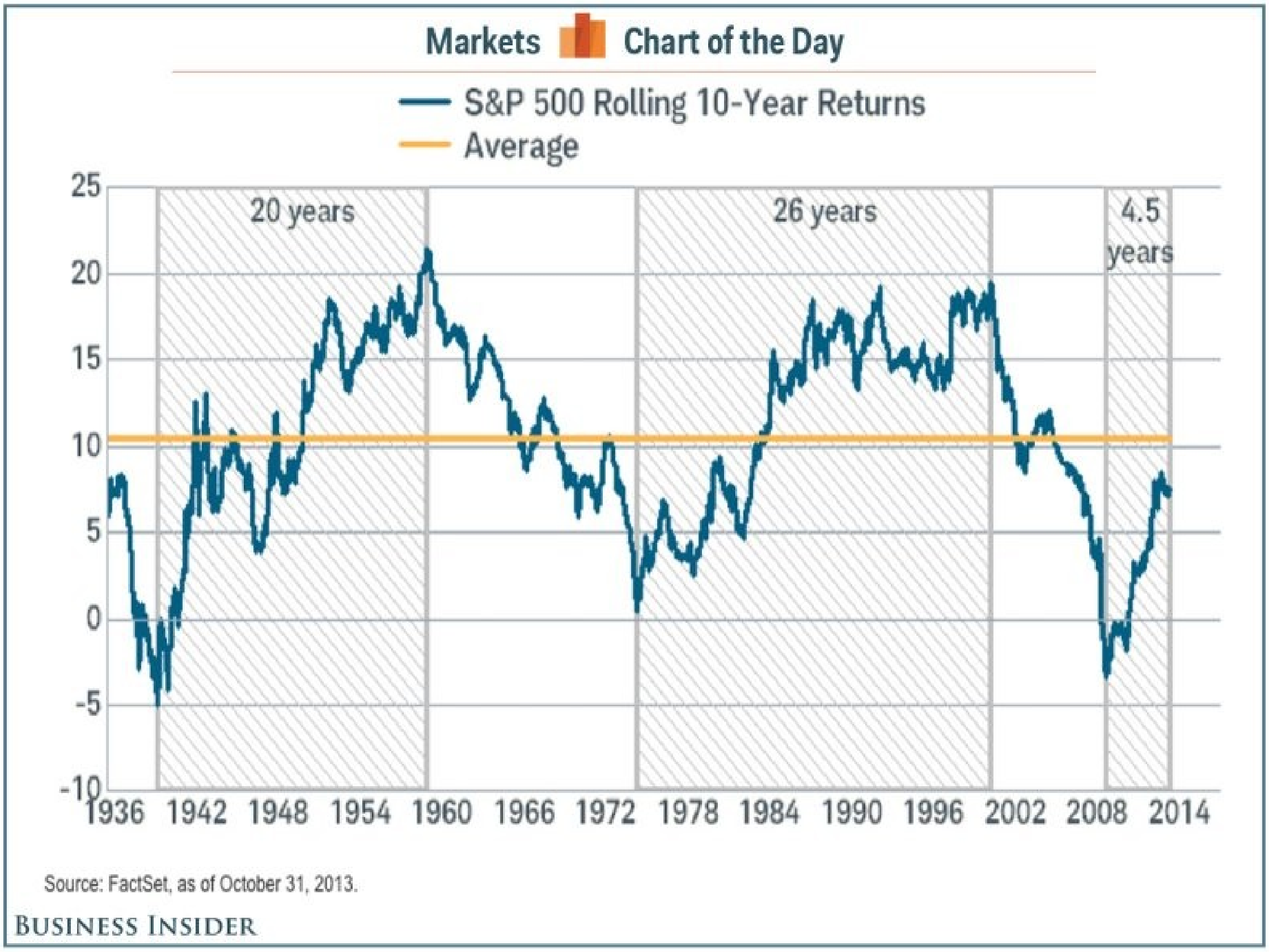
Introduction



This graph, from the book *Stocks For The Long Run* by Jeremy Siegel (Siegel 2007, 2013), demonstrates that the long term return from stocks greatly exceeds other common asset classes over the past two plus centuries. Why then do financial advisors routinely recommend diversification of investments, and why do we sometimes even hear “cash is king?”



This second graph, from Liz Ann Sonders via Business Insider (Ro 2013), demonstrates why people diversify their investments. While returns from stock investments look consistent over a time frame of 211 years, over the shorter term, such as one's adult life, these returns can be quite volatile. Although the original intent of the above graph was to argue that the market is in a long term uptrend, it also shows that there are long periods where the 10-year return of the market is falling. Should you be unlucky enough to enter the market at the start of a downtrend, it could be quite some time before you broke even. In recent memory, a person who entered the market at the height of the technology boom may still be waiting to recover his or her initial investment.

It is a quirk of human behavior that many people prefer lower draw-downs (maximum negative excursion) to higher total returns. When faced with a choice between two investments, one yielding an 80% chance of a $1,000 return, and one yielding a 100% chance of a $600 return, a majority of people choose the latter, even though on average it will yield a lower total return. Bernie Madoff's scheme wooed sophisticated investors by promising below average volatility and drawdown, even though his total return was often less than that of the S&P 500 (Madoff, Wiki), and the method he said he employed would not make money in a down market.

Despite the substantial coverage given to buy-and-hold strategies, the average blended equity and fixed-income investor significantly lags broad market averages and barely beats the rate of inflation (Hanlon 2014, Jaffe 2014, Maye 2012). The authors of these papers conclude the average investor does in fact time the market, but driven more by emotion than logic, and therefore does so poorly.

There is a middle ground between full time investment in the stock market and diversification to decrease volatility (and returns). Methodically developed, statistically verified mechanical, or automated, trading systems can direct investments into the stock market during periods of market uptrends, and to short stocks or direct capital into cash or other financial classes during periods of market downtrends. Two keys to successful market timing are developing systems which adapt to changing market conditions, and the iterative testing of systems to demonstrate their success is due to design rather than statistical chance.

To Time or Not To Time

There are two types of investors. The first type claims that the financial markets can not be timed; that their movements are random and unpredictable, and that market investment is worthwhile only because the long term trend is up. Their advice is to buy assets and hold them for the long term. This type of investor is subject to the whims of the market, and will suffer long periods of stagnant or negative growth. The second type of investor uses a variety of tools and techniques to determine buy and sell points, and move from long to cash to short positions. If one is willing to invest the time and effort to develop or evaluate profitable trading systems, the rewards can be great.

In the realm of financial markets, the random walk theory and efficient market hypothesis survive in spite of considerable evidence of their fallacy (Murphy 2004) . The random walk theory states that the stock market cannot be predicted. The efficient market hypothesis states that share price reflects all relevant information and therefore as a corollary one cannot outperform the overall market (Zweig 1997). Those who believe these suppositions would conclude that timing the financial markets is pointless, and the only viable strategy is buying stocks and holding long term (O'Shaughnessy 1997). A true believer might even argue that it doesn't matter what stock you buy, since all are priced efficiently.

This buy-and-hold advice has been repeated often by many offering financial advice. Yet there are numerous counterexamples to its veracity. If the markets were truly efficient, stocks prices would move smoothly up and down in concert with the state of the economy. Bubbles and crashes would occur infrequently. Inter-market arbitrage would not be possible, nor would it be possible to exceed buy-and-hold returns using simple trading systems, such as the 4% swing system (Fosback 1991, Arnold 1993). If the markets of the past fifteen years have told us anything, it is that buy-and-hold is not an optimal strategy.

Technical Analysis

Classical technical analysis teaches that the best trading systems are robust and applicable across different instruments and time frames. This is in part to assure that a particular trading system is not curve-fit to a single time series, and will therefore work with future data. However, there is no reason that a system can not be trained on a particular time series and interval, as long as the validity of the system is later verified to work on out-of-sample data, data the system has not seen during trading. The challenge, given the relatively short time series available for most financial instruments, as well as the changing nature of these instruments over time, is to assure that the success of a system in trading out-of-sample data is statistically significant and not a random occurrence (Arnold 1993, Aronson 2007).

Trading systems which use technical indicators such as moving averages and oscillators need to define parameters for indicators and state how indicator(s) are evaluated to produce trading signals. For example, a simple system might state: Buy when the price rises above a 20 period simple moving average. A more complex system might use more indicators, similar indicators with different parameters, and use these indicators in rules to produce buy and sell signals. The assignment of parameter values, the weighting of indicators, and how indicators are combined into a trading signal are often arbitrary and suboptimal. This may lead to a system using more inputs, and thus having more degrees of freedom, than is necessary. Such a system may be susceptible to curve fitting and prove more difficult to validate (Zirilli 1997). All things being the same, a trading system using a smaller number of inputs is superior to a similarly performing system using more inputs.

Neural Networks and Genetic Algorithms

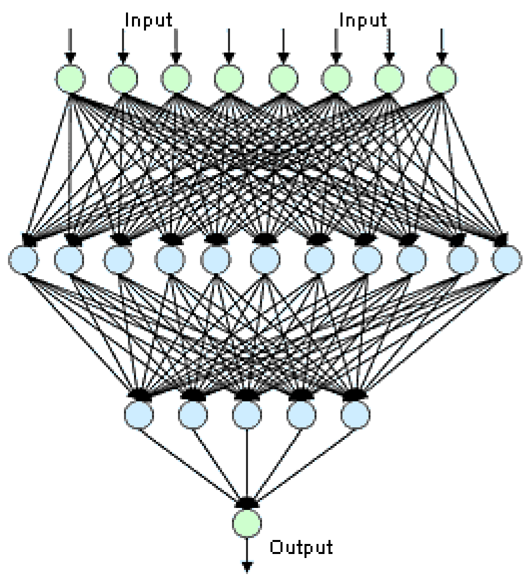


Image 1: A four level feed forward artificial neural network

Artificial neural networks (ANN) and genetic algorithms (GA) can assist in designing trading systems which have as few degrees of freedom as necessary. ANNs can discover relationships between indicators (inputs) and (profitable) trading signals which may be nonlinear and not be obvious to inspection (Fishbein 2005). GAs can help optimize systems and do so faster than exhaustive searches. This speed is particularly important when GAs and ANNs are combined in an iterative cycle of indicator optimization (GA) and indicator mapping to trading signals (ANN). Elimination of inputs to just before the point of decreasing profitability will result in a system with the fewest necessary degrees of freedom.

Assume that one or more indicators are chosen, and a hybrid ANN/GA system produces a trading system which is profitable for the interval over which the system is trained. The next step is to test the system out-of-sample, using data not used during training. The success or failure over a single out-of-sample interval is not sufficient to evaluate a system. It is little more than a role of the dice. Results may be anomalous and not representative of the ability of a system over the long-term. A system may be profitable or not over a single out-of-sample test and yet say little about the its ultimate profitability.

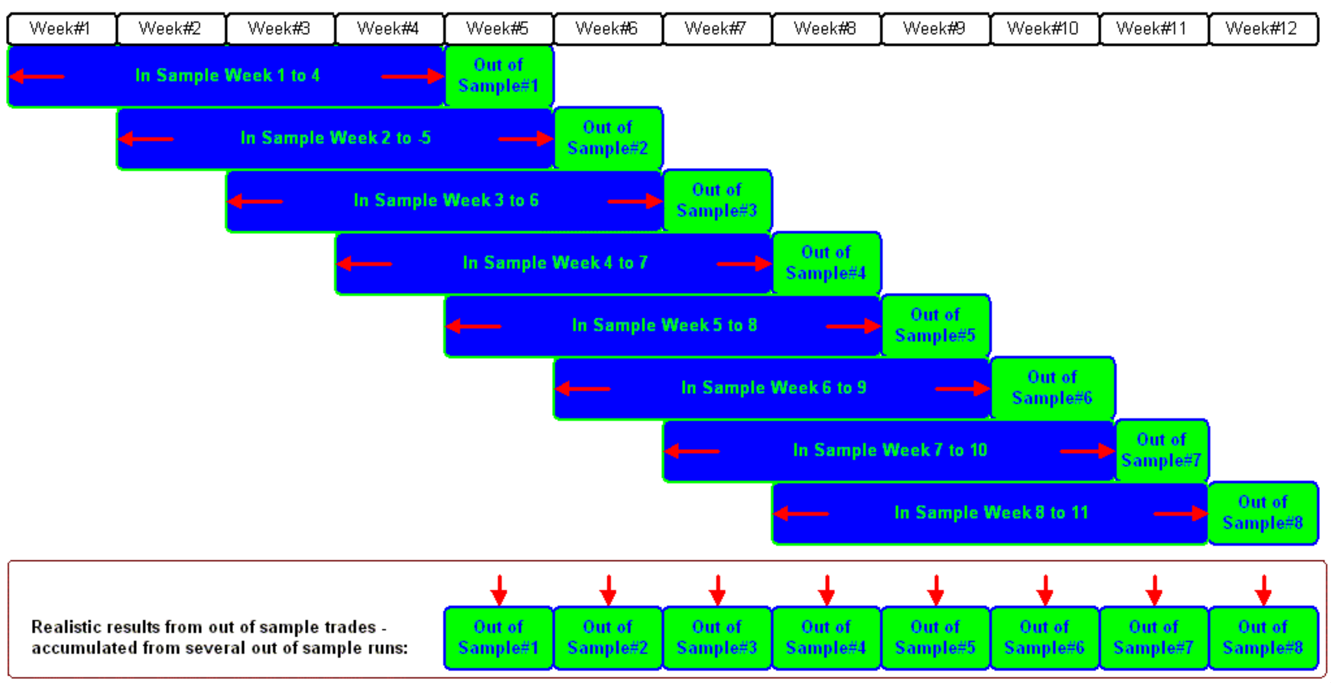
Testing Trading Systems

A prudent person should test a trading system before committing to using the system for live trading. The rigorousness of the testing program can determine the success of the system in live trading. Contrary to popular opinion, a record of successful live trading is not in of itself sufficient proof of the validity of a system. Such success may be a statistical fluke, and not representative of the future long term performance of a system.

The simplest test of a trading system is its application to a single time range. The statistical significance of this result may vary depending on the number of bars tested. There is also the concern that the system may have been developed with knowledge of the test period, and therefore has been tailored to the known data. The ability of such a system to perform into the future, with previously unseen data, may be compromised.

Adaptive systems which are trained on known data introduce another concern. If the system is trained and then tested on the same data set, it has not been demonstrated that the system will be effective with unseen, future data, such as occurs in real life trading. It is necessary to hold out a portion of the data for testing the system after training. The progressive process of testing a system on a portion of the held out data, and then incorporating the held out portion into the training set, is referred to as walk-forward testing.

Walk-forward testing trains a system over a portion of the available market data, then tests over a small interval forward in time. The system is then retrained using the original training interval and the out-of-sample segment, then tested out-of-sample over the next interval of market data. The process is repeated until the available data is exhausted, and the results over multiple out-of-sample tests are calculated, as shown below.



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In testing trading systems for financial markets, a common limitation is the lack of sufficient data for testing. The trading year contains approximately

250 trading days, so an end-of-day system for a stock with a 10 year history would contain appoximately 2500 data points. This may be an insufficient number to generate a statistically significant test.

The fact that a system remains profitable over a number of walk-forward intervals doesn't in itself guarantee the system will remain profitable in the future. Even if enough data is available to reach levels of statistical significance, there is no certainty that the future will look like the walk-forward intervals. Consider the system mentioned earlier: Buy when the close > 20 period simple moving average. This system performs well in a smoothly trending market, and poorly in most other markets. If the walk-forward periods encompass only a smooth uptrend, the system will show a successful walk-forward test and yet fail in a market which does not resemble the walk-forward periods.

Monte Carlo Testing

What is needed is a unlimited stream of market data which would represent all potential market conditions the system might be asked to trade under. While actual data is limited, Monte Carlo testing provides a method to generate synthetic data which closely simulates the data characteristics of the actual market under test, as detailed by several authors (Chande 1997, Aronson 2007). To summarize, synthetic data is created by picking an arbitrary starting value, and then incrementing the open, high, low and close for each period by a change or percentage change chosen from a bar in the actual data, chosen randomly for each period. By this method, limitless synthetic market data which retains characteristics of the original data can be produced. The system can be trained and tested over a number of synthetic data series to the desired level of statistical significance.

Example of ANN/GA Trading System with Monte Carlo Testing

The following example shows the construction of a trading system using ANNs and GAs, which is then validated using walk-forward and Monte Carlo testing. The system is an end-of-day trading system which uses three well known technical indicators (Colby 2002) and the closing price of the stock:

1. 4 Percent Swing System
2. MACD – Moving Average Convergence - Divergence
3. RSI – Relative Strength Index

To train and test the system, 10 years of daily data for the exchange traded funds QQQ (Nasdaq-100), SPY (S&P 500), and IJR (S & P Small Cap 600) were used. Having specified the four inputs, the software evaluates neural networks with indicators and indicator parameters chosen by a genetic algorithm in an iterative fashion (Fishbein 2008). An initial 2 month out-of-sample period is specified, and the out-of-sample results shown in the table below:

4 input ANN/GA system	*# walk-forward periods*	*# synthetic data series*	*Average yearly return*	*Average Winning Trades*	*Average Max Drawdown*
IJR			19.6%	63.2%	9.8%
QQQ			25.6%	64%	14.3%
SPY			16.8%	66%	6.4%

All of the exchange traded funds showed positive returns. While encouraging, these results alone do not ensure the system would be profitable in future markets. As previously discussed, the single out-of-sample period might have characteristics particularly suitable to the design of the system. It would be useful to test the system against a number of out-of-sample scenarios.

Walk-forward testing was next performed using 40 periods of 40 samples each. In the initial test, data up to the last 1600 trading days was used to optimize the system. Then, the next 40 trading days were used as an out-of-sample test, in which the optimized system was used to trade these 40 days without any further optimization. The indicator parameters and network weights were maintained as determined during optimization, and the results of the out-of-sample test recorded. Next, the system was re-optimized using the original optimization period plus the 40 days previously used for the out-of-sample test, and the new system tested out-of-sample on the next 40 trading days. This process is repeated a total of 40 times, and the trading results for the 40 out-of-sample periods tabulated.

IJR		19.6%	63.2%	9.8%
QQQ		25.6%	64%	14.3%
SPY		16.8%	66%	6.4%
IJR	40	18.8%	69%	9.8%
QQQ	40	28.4%	65%	12.2%
SPY	40	14.4%	62%	9.9%

Profitability, the percentage of winning trades, and the maximum drawdown remained similar to the initial test. The results so far are favorable and this system has potential to be a useful tool.

The number of walk-forward tests that can be performed is limited by the length of the trading history for the instrument under test. Sufficient data must be available for the initial optimization. It is also possible that even a lengthy walk-forward period may not adequately represent market conditions the system may see in the future. Monte Carlo testing offers a method to generate endless data which closely matches the characteristics of the original data series. The intricacies and applications on Monte Carlo testing are addressed elsewhere (Aronson 2007).

For each exchange traded fund under test, the method described by Chande (1997) was used to construct 500 synthetic data series of 10 years in length. Each data series was then used to train the hybrid artificial neural network/genetic algorithm system described above, with the last two months of data used as an out-of-sample test. The average annualized return, percentage of winning trades, and maximum drawdown were calculated for each out-of-sample period for each ETF and summarized in the table below:

4 input ANN/GA system	*# walk-forward periods*	*# synthetic data series*	*Average yearly return*	*Average Winning Trades*	*Average Max Drawdown*
IJR			19.6%	63.2%	9.8%
QQQ			25.6%	64%	14.3%
SPY			16.8%	66%	6.4%
IJR	40		18.8%	69%	9.8%
QQQ	40		28.4%	65%	12.2%
SPY	40		14.4%	62%	9.9%
IJR		500	16.8%	64%	10.3%
QQQ		500	27.3%	58%	14.4%
SPY		500	13.8%	63%	12.2%

Results for each fund remained positive and did not show significant variation from those obtained with walk-forward testing. Average maximum drawdown was higher in Monte Carlo testing than in walk-forward testing. Results from Monte Carlo testing may lag behind those from live data as synthetic scenarios encompass a range of challenging conditions not seen with the live period. These results from Monte Carlo testing give added confidence that the system produces reproducible results and its results do not represent a statistical anomaly (Masters 2009).

Summary

Buy-and-hold investing strategies for the stock market can be improved upon. Systematic mechanical trading provides one way to time the market, and lends itself to testing and validation. The combination of ANNs and GAs offers a unique way to develop powerful trading systems. A hybrid ANN/GA system using the 4% Swing System, MACD, RSI and closing price was described. The system generated positive returns in the initial out-of-sample test period. A walk-forward test extending back 1600 trading days was performed, again showing positive returns for each instrument. Finally, Monte Carlo testing was performed using 500 synthetic data series for each instrument, showing positive returns. Timing the stock market using a mechanical trading system based on ANNs and GAs provides a statistically significant increase in trading returns over a buy and hold strategy. Similar results were demonstrated using a system with different inputs in earlier papers (Fishbein 2009, Fishbein 2014).

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