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A Fuzzy Logic Stock Trading System Based On Technical Analysis

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A FUZZY LOGIC STOCK TRADING SYSTEM

BASED ON TECHNICAL ANALYSIS

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Abstract

Technical analysis of financial markets involves analyzing past price movements in order to identify favorable trading opportunities. The objective of this research was to demonstrate that a fuzzy logic stock trading system based on technical analysis can assist average traders in becoming successful by optimizing the use of technical indicators and trading rules that experts use to identify when to buy and sell stock. Research of relevant literature explored the current state of knowledge in methodologies for developing and validating trading systems using technical indicators and fuzzy logic trading systems, providing guidelines for the development and evaluation of the system. Evaluation of the system confirmed that fuzzy logic can have a positive contribution to a successful trading system, and that once a successful trading system has been developed and verified an average trader can be successful by simply following the trading system’s buy and sell signals. The trader need not be an expert at interpreting the underlying technical indicators or react to price movements emotionally. The trading decisions are made by the trading system, so the only decision that the average trader need make is whether there is enough confidence in the system to commit real money in live trading. Suggestions for future research include improvements in accuracy and flexibility, and investigation of additional trading models and filters.

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Chapter 1 – Introduction

Technical analysis of financial markets involves analyzing past price movements in order to identify favorable trading opportunities. Traders commonly use a variety of technical indicators (Schwager, 1999, p. 110) to make buying and selling decisions. A *technical indicator* is a mathematical formula that calculates a series of price based data points that represent a pattern over some period of time. A technical indicator usually has a set of corresponding trading rules based on trigger conditions that signal a buy, sell, or hold bias for each data point.

Many regard technical analysis as more of an art than a science. There are hundreds of technical indicators. Interpretation of signal trigger conditions can be subjective. Some indicators work better than others, consistently signaling the best times to buy and sell. It is usually advisable to use multiple indicators in combination to provide a more balanced approach for a variety of trading conditions. Expert traders are skilled at interpreting the various technical indicators and applying trading rules, while average traders can find it difficult to duplicate the success of experts due to the complexity involved (Colby & Meyers, 1988, pp. iii, 17; Edwards & Magee, 1992, pp. 12, 345-348; Murphy, 1999, pp. 11, 17; Schwager, 1999, pp. 7-16).

Emotions are the cause of many common errors that traders make including overtrading, buying too early, and selling too late. A mechanical trading system can help traders avoid many common errors by eliminating emotion from trading. A mechanical trading system can reduce the complexity of trading by implementing a consistent trading strategy, providing trading signals based on technical analysis of a stock's current trading conditions (Schwager, 1999, p. 227-228).

There has been considerable research on using fuzzy logic techniques for trading (Ahmad, Gayar, & Elazim, 2006; Cheung & Kaymak, 2007; Doeksen, Abraham, Thomas, &

Paprzycki, 2005; Dourra & Siy, 2002; Gamil, El-fouly, & Darwish, 2007; Ghandar, Michalewicz, Schmidt, To, & Zurbrugg, 2009; Khcherem & Bouri, 2009; Li & Yang, 2008; Zhou & Dong, 2004). A number of trading systems have been developed that make use of fuzzy logic techniques. Scribner Software's (2010) TekView Explorer software uses fuzzy logic to create and back-test trading strategies. VonAltrock (1997, pp. 211-220) used the fuzzyTECH software to create a fuzzy logic stock analysis system that incorporated technical chart analysis to make buy and sell decisions.

This research seeks to demonstrate that a fuzzy logic trading system based on technical analysis can assist traders in becoming successful by optimizing the use of technical indicators and trading rules that expert traders use when trading stock, thereby reducing the complexity for average traders. The resulting trading system will be a valuable tool that average traders can use to successfully trade stocks even though they may not necessarily be expert traders.

The objective of this research is to develop a stock trading system that uses fuzzy logic to identify when to buy or sell a stock based on technical analysis. The resulting system will then be evaluated to determine if its use can assist traders in becoming successful at trading stocks.

This research will contribute to the fields of technical analysis and software engineering by providing a detailed account of the analysis and development of such a system. The proposed system is essentially a solution to the problem of time series analysis (Murphy, 1999, pp. 18-19) as applied to stock prices. The system could serve as a basis for evaluating solutions to other time series analysis problems, by adapting it for use with other data sets and developing prediction models for specific problem domains.

Chapter 2 outlines the research and review of relevant literature; i.e. basic principles of technical analysis of financial markets, using technical indicators to make trading decisions, methodologies for developing and validating trading systems, basic elements of fuzzy logic, and using fuzzy logic in trading systems.

Chapter 3 explains the methodology used to carry out the research, developing and evaluating a fuzzy logic stock trading system based on technical analysis, guided by the current state of knowledge provided by the literature review outlined in chapter 2.

Chapter 4 presents analysis and results achieved from the research data collected, and discusses insights and observations relevant to the project.

Chapter 5 provides interpretation of the data as it relates to the research objective and presents the research findings, lessons learned, limitations and shortcomings identified, and the need for further research.

Chapter 2 – Review of Literature and Research

2.1 Introduction

The design of a fuzzy logic stock trading system based on technical analysis integrates concepts of technical analysis of financial markets with elements of fuzzy logic from the artificial intelligence field. Technical indicators used to make trading decisions form the foundation of the system along with the methodologies for developing and validating trading systems. Fuzzy logic principles enhance the trading decision logic of the system with fuzzy versions of traditional technical indicators.

2.2 Technical analysis

Technical analysis of financial markets involves analyzing past price movements in order to identify favorable trading opportunities. One of the primary tools of technical analysis is the chart which displays price, and usually volume, in a simple time series graph as illustrated in Figure 1. A trader that uses technical analysis is often referred to as a technician or chart analyst. In the commodity and financial markets, it is estimated that for about one third to seventy percent of the time, prices tend to trade in a sideways or range-bound pattern. When not range-bound, prices tend to display powerful and sustainable trends, offering traders low risk and high reward opportunities. Since market trends offer the best profit opportunities, the objective of chart interpretation is to identify price patterns that indicate significant trends and impending trend changes. *Trend* refers to the general direction the market is moving. Markets, however, do not move in a straight line. They move in a series of zigzags that resemble a series of waves with peaks and troughs. The direction of those peaks and troughs constitute the market trend. An uptrend is defined by a succession of higher highs and higher lows, where each relative high is higher than the preceding high and each relative low is higher than the preceding low. Price dropping below a previous low serves as a warning or clue that the uptrend may be ending. Similarly, a downtrend is defined by a succession of lower lows and lower highs. Price breaking above a previous high signals a possible end to the downtrend. A flat, horizontal, sideways, or trendless market movement reflects a relative balance in price action, and is commonly referred to as a *trading range* (Colby & Meyers, 1988, p. 5; Murphy, 1999, pp. 42,49-51; Schwager, 1999, p. 33; Weissman, 2005, pp. 10-11).

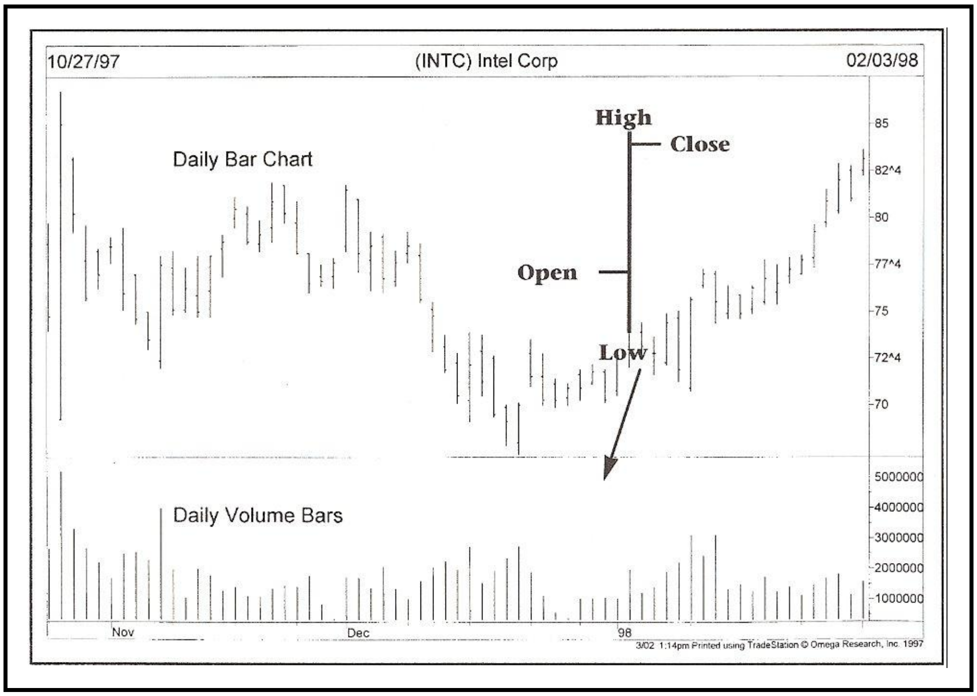


Figure 1 - Intel stock chart (Murphy, 1999, p. 42)

2.2.1 Chart analysis

Market technicians analyze patterns in price charts to gauge whether the price is trending up or down, in a trading range, or breaking to the up or down side. Charts typically display price on the upper portion of the graph and other data such as volume on the lower portion of the graph. A common format for the price graph displays bars (Renz, 2004, pp. 40-42; Schwager, 1999, pp. 17-19) that indicate the price open, high, low, and close values, as shown in Figure 2. Each bar represents one data point in time, such as daily, weekly, or monthly.

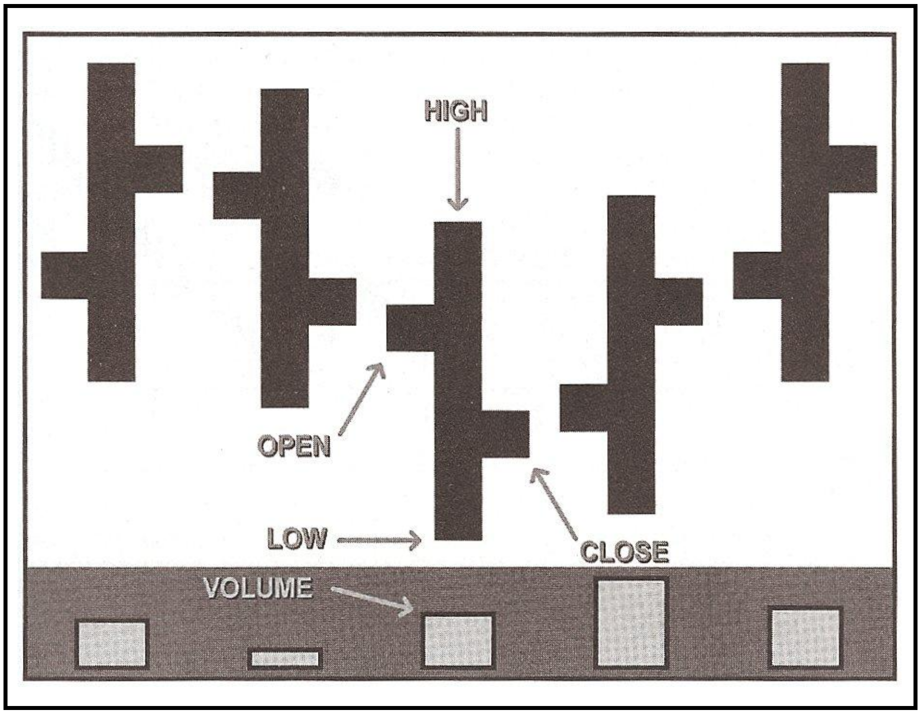


Figure 2 - Chart bars (Renz, 2004, p. 41)

An example chart pattern is the bearish flag formation (Renz, 2004, pp. 58-59) shown in Figure 3 that starts with an uninterrupted down trend followed by a trading range lasting for some period of time. The horizontal support and resistance lines can slope up or down slightly but are usually roughly parallel. Price breaking below support with a corresponding surge in volume usually indicates that the down trend is about to resume.

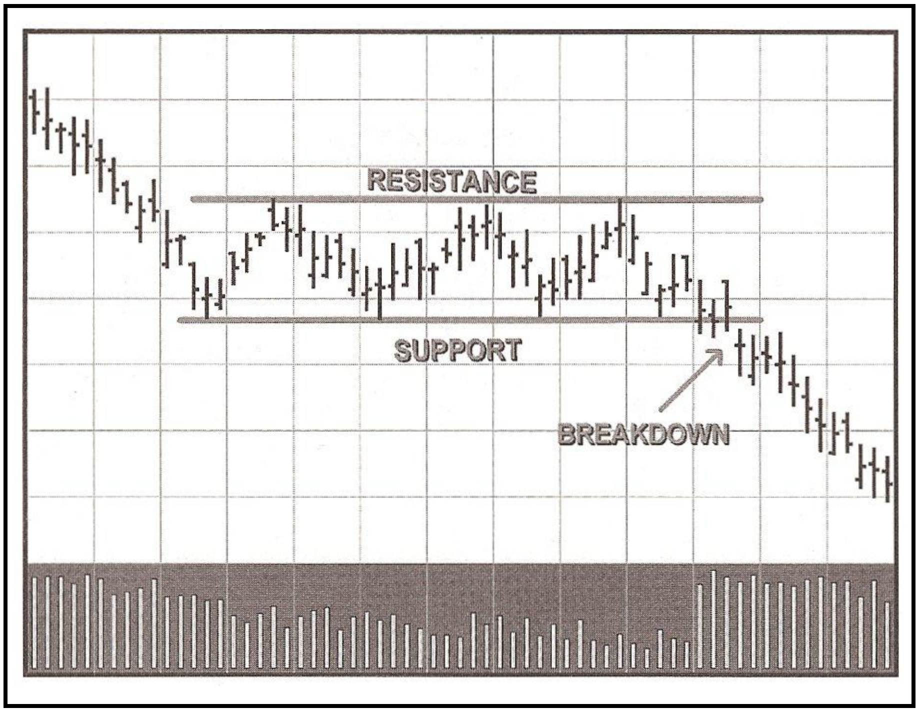


Figure 3 - Bearish flag (Renz, 2004, p. 59)

The inverted head and shoulders pattern, as shown in Figure 4, is a bottoming formation that can present a buying opportunity. Price breaking above the neckline with high volume signals a turnaround in the trend, and an opportunity to buy at the start of the new uptrend (Edwards & Magee, 1992, pp. 80-84; Renz, 2004, pp. 75-77).

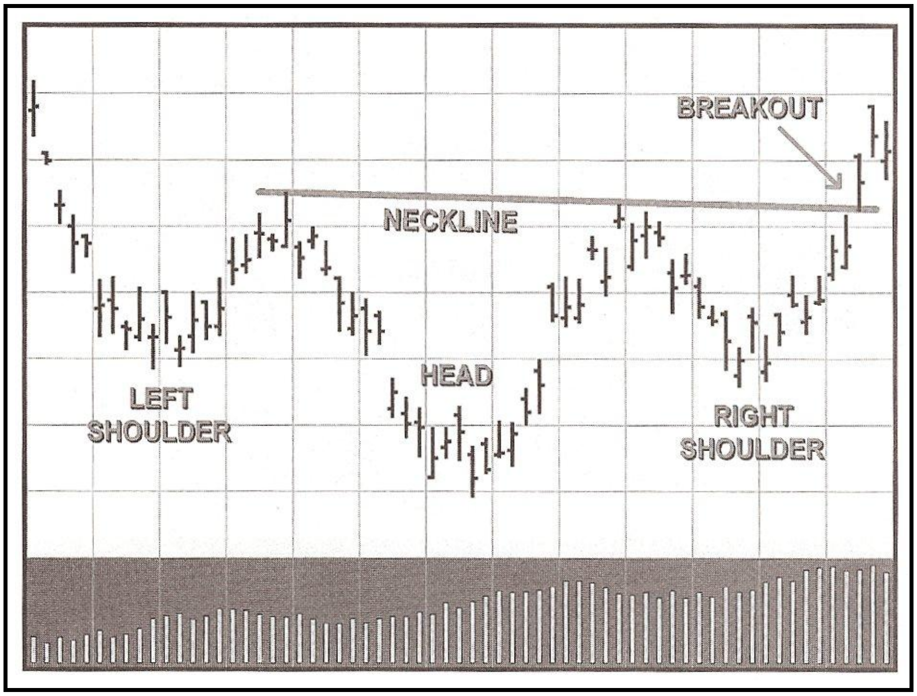


Figure 4 - Inverted head and shoulders (Renz, 2004, p. 77)

2.2.2 Technical indicators

The application of technical analysis based on chart analysis depends on individual interpretation. Without clearly defined rules, technical analysis procedures are subject to different interpretations and applications and thus cannot be utilized unambiguously by different people (Colby & Meyers, 1988, p. 12; Schwager, 1999, p. 14).

Traders frequently supplement chart analysis with a variety of statistical calculations, called technical indicators, to evaluate price activity and make buying and selling decisions (Colby & Meyers, 1988, p. 5; Schwager, 1999, p. 110). A *technical indicator* is a mathematical formula that calculates a series of price based data points that represent a pattern over some period of time. A technical indicator usually has a set of corresponding trading rules based on trigger conditions that signal a buy, sell, or hold bias for each data point. For example, the *moving average* is a widely used technical indicator calculated by taking the average of the price over a certain number of the most recent time periods (Murphy, 1999, pp. 195-198). A stock price moving above its 30 day moving average might trigger a buy signal and price moving below its 30 day moving average might trigger a sell signal.

Mathematical technical indicators usually fall into one of two categories, trend-following indicators and mean reversion or counter-trend indicators. Trend-following indicators such as moving averages profit when prices trend either up or down for a relatively long period of time. Mean reversion indicators such as momentum oscillators capitalize on prices becoming overextended followed by reversion back to the mean (Weissman, 2005, pp. 16-17).

The following includes discussions of just a few technical indicators commonly referenced in the literature. A more complete reference for these and many more technical indicators can be found in Achelis (2001, pp. 45-373), Colby & Meyers (1988, pp. 61-572), and Murphy (1999, pp. 195-263), where each indicator is explained along with its interpretation, calculation, and examples.

2.2.2.1 Trend-following indicators

Trend following indicators, such as moving averages, are lagging indicators. They work very well during significant price trends, providing good low risk profit opportunity in major trends. They do not predict future price changes; they simply indicate what the most recent price trend is. The buy and sell signals that they generate always occur late. They do not generate signals until after a trend has been established. The trader will always miss the first part of a price move and may surrender significant portions of profit before an opposite signal is given when the trend reverses. The tradeoff of sensitivity will determine how fast signals are generated. Less data included in the calculation of the indicator increase sensitivity and generate faster signals, resulting in quicker response to trend reversals and tend to maximize profit on valid signals but also generate more false signals (Achelis, 2001, p. 33; Schwager, 1999, p. 229).

2.2.2.2 Momentum indicators

A central concept in technical analysis is *momentum* which represents the rate of change of price, or price velocity, and is a leading indicator of a change in trend direction. Typically a major market cycle starts a new uptrend with very high and rising momentum. The positive price velocity gradually tapers off until the price reaches its peak. This is referred to as bullish exhaustion (Colby & Meyers, 1988, p. 5).

Price based momentum indicators (also called oscillators) represent the rate of change of price movement by performing some calculations on past price data over some period time, the look-back period, and comparing the current price with the price data over the look-back period. It is important to note that momentum indicators represent momentum trends, not price trends. Momentum and price do not always trend together, they may diverge. For example, a momentum indicator may make a bearish reversal and decline even though the price continues to trend higher but at a slower rate of change. Since momentum reversals do not always coincide with a corresponding price reversal, one should not assume a price reversal when momentum reverses (Miner, 2009, p. 11).

As market trends weaken, prices can become choppy and move sideways for several weeks or months, and trend-following indicators become less useful. Momentum oscillators can be very useful when prices are trading sideways in a trading range. Some momentum indicators have zones of extreme high and low values that can give signals in advance of an actual top or bottom. The zones are usually partitioned at high and low cut-off points to identify overbought, oversold, and neutral regions. They can generate trading signals when price becomes overextended in the overbought or oversold zones, when the oscillator is in an overbought or oversold zone and diverges from price, or when the oscillator crosses the zero (midpoint) line.

Momentum indicator signals are usually used as prerequisite conditions in combination with other indicators to provide a confirmation of bullish, bearish, or neutral mode. Oscillator signals work best when traded in the direction of the underlying market trend (Colby & Meyers, 1988, p. 15-16; Murphy, 1999, pp. 225-251).

Miner (2009, pp. 12-47) advocates a momentum strategy using two time frames, where trading signals are generated in the direction of the larger time frame momentum, if not in the overbought or oversold region, following a smaller time frame momentum reversal. Most common momentum indicators can be used for this strategy such as stochastic (Stoch), relative strength index (RSI), and moving average convergence divergence (MACD).

2.2.2.3 Moving averages

The moving average is one of the most versatile and widely used technical indicators, and is commonly used as the basis for trend following systems. The moving average is calculated by taking the average of the price over a certain number of the most recent time periods. The closing price is most commonly used to calculate moving averages. The moving average is a trend follower, its purpose is to signal when an old trend has ended or a new trend has begun, and track the progress of the current trend (Murphy, 1999, pp. 195-198).

Moving averages can be used to determine the general direction or trend of a market based on its recent price movement. Moving averages represent smoothed price series data over a period of time, making trends and meaningful turning points more obvious. Longer-term investors typically use the 200-day moving average, buying when price moves above the 200-day moving average and selling when price moves below the 200-day moving average. This simple method is also commonly used to complement other confirming technical indicators (Colby & Meyers, 1988, pp. 14-15; Renz, 2004, p. 92).

Of the many variations of moving averages, the simple moving average is the most widely used and easiest to calculate because it gives equal weighting to each data point within the data set. The moving average generates trading signals when the price crosses the moving average, a buy signal when price crosses above the moving average and a sell signal when the price moves below the moving average. The problem with longer-term moving averages is that they lag price changes making them slow to respond to changing trends. Shorter-term moving averages have quicker response but can generate more false signals. The linear weighted moving average and exponential moving average can reduce lag by giving a larger weighing factor to more recent data (Murphy, 1999, pp. 199-202; Weissman, 2005, p. 18).

Figure 5 illustrates a 15-month simple moving average of the Dow Jones Industrial Average (DJIA) over about a 30 year period, from1970 through late 1999. Buy signals are shown with up-arrows when the price crosses above the moving average and sell signals are shown with down-arrows when the price crosses below the moving average (Achelis, 2001, pp. 203-204).

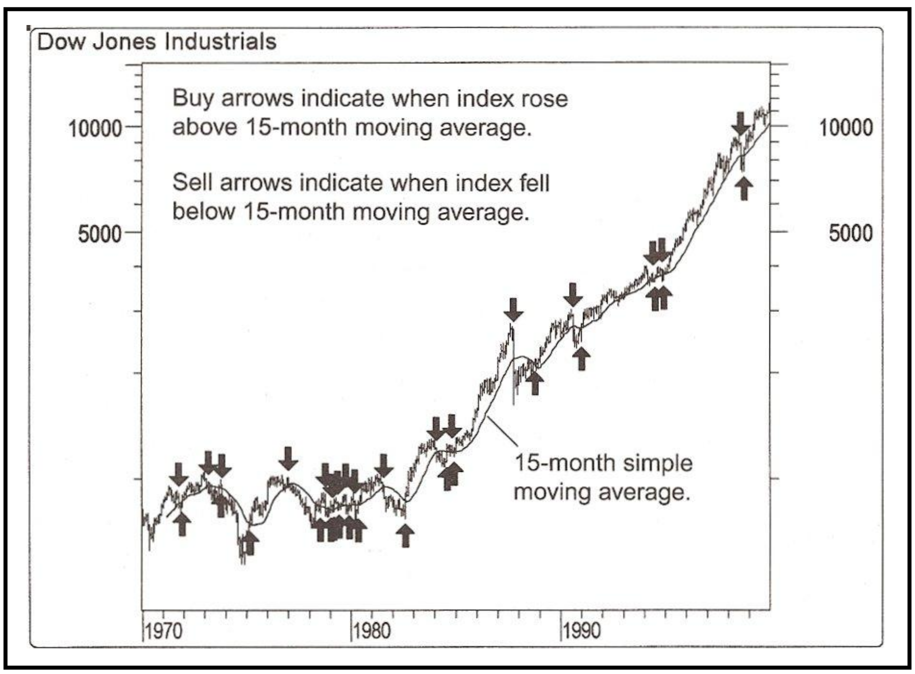


Figure 5 - DJIA 15-month simple moving average (Achelis, 2001, p. 204)

One method to try to avoid moving average false signals is to wait a certain period of time after a signal is given before acting on the signal (Weissman, 2005, p. 19). For example, a buy signal might be generated when price moves above the moving average for three consecutive days.

Another popular method to filter out moving average false signals is to require a certain amount of penetration beyond the moving average, usually referred to as moving average envelopes. The envelopes are offset above and below the moving average by a certain amount (Weissman, 2005, p. 21). For example, a sell signal might be generated when price moves below the moving average by three percent. Envelopes can also be used as a countertrend indicator by viewing the penetration beyond the envelope as an indication that the market has overextended with the expectation that it will eventually revert back toward the moving average (Murphy, 1999, p. 207; Weissman, 2005, p. 21).

Comparing two moving averages works especially when you may not have other technical clues, such as for rounding tops and bottoms (Renz, 2004, p. 93). The two moving average crossover method generates a signal when a shorter moving average crosses a longer-term moving average. For example, a buy signal might be generated when the 10-day moving average crosses above the 20-day moving average. The three moving average crossover requires three moving averages to be aligned before a signal is generated. For example, in order to generate a buy signal, the 5-day moving average must cross above a 10-day moving average, and the 10-day moving average must cross above the 20-day moving average. Common time periods for the three moving average crossover method include 5-10-20-day and 4-9-18-day time periods (Murphy, 1999, pp. 203-206; Weissman, 2005, pp. 23-24).

2.2.2.4 Moving average convergence divergence

The moving average convergence divergence (MACD) is a common indicator which includes a MACD line and a MACD signal line. The MACD line is calculated as the difference between a shorter-term 13-period exponential moving average and the longer-term 26-period exponential moving average. The MACD signal line is the 9-period exponential moving average of the MACD line. The basic MACD trading rule generates a buy signal when the MACD line crosses above the signal line and a sell signal when the MACD line crosses below the signal line (Weissman, 2005, pp. 26-27). Another popular MACD trading rule generates a buy signal when the MACD line crosses above zero and a sell signal when the MACD line crosses below zero. Figure 6 illustrates the MACD for Whirlpool. The up-arrows show buy signals when the MACD line crosses above the signal line and the down-arrows show sell signals when the MACD line crosses below the signal line (Achelis, 2001, pp. 199-200).

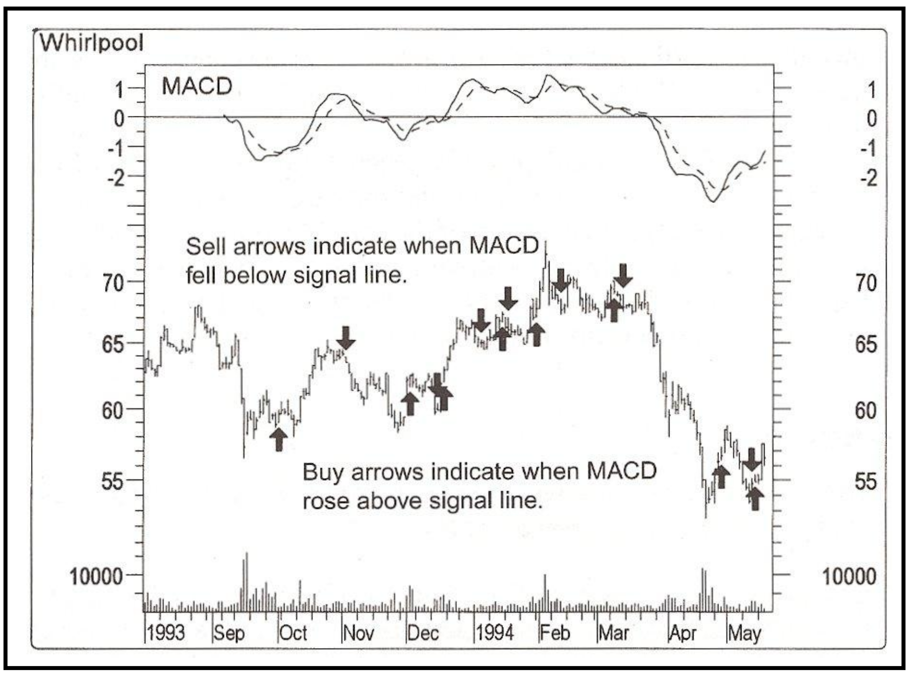


Figure 6 - Whirlpool MACD (Achelis, 2001, p. 200)

2.2.2.5 Directional movement indicator and average directional movement index

The directional movement indicator (DMI) attempts to measure market strength and direction. It uses each period's net directional movement, which is the largest part of a period's range that is outside the previous period's range. There are separate calculations for positive movement (+DI) and negative movement (-DI). When +DI is greater than -DI, the market is trending higher and when –DI is greater than +DI, the market is trending lower. A buy signal is generated when the DMI crosses above the zero line and a sell signal when the DMI crosses below the zero line. The average direction movement index (ADX), plotted on a 0-100 scale, and is an index of the relative strength of the trend, measuring the degree of directional movement. It is derived by applying a 9-period smoothing of the result of dividing the difference between the absolute value of +DI and DI by the sum of +DI and DI. A rising ADX line means the market is trending and a falling ADX line indicates a non-trending market. Figure 7 illustrates the ADX for the S&P 500 Stock Index. The ADX falling from above 40 (down-arrow) indicates the beginning of a sideways trading range and the ADX rising from below 20 (up-arrow) indicates continuation of the trend (Murphy, 1999, pp. 384-387; Weissman, 2005, pp. 27-28).

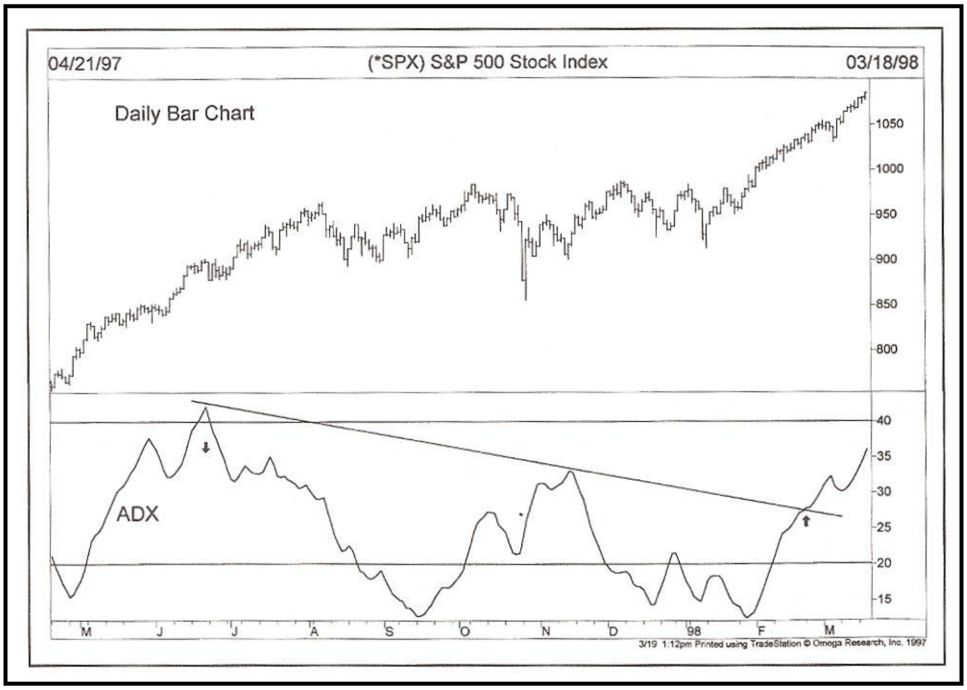


Figure 7 - S&P 500 stock index ADX (Murphy, 1999, p. 384)

2.2.2.6 Price channel breakout

The channel breakout is a simple trend following trading system that generates signals when a trend is already established. Trading signals are generated when the price exceeds the highest high or lowest low of the past n periods (Weissman, 2005, p. 30). Figure 8 illustrates a fast breakout system for IBM where n=7 days. Up-arrows show buy signals when price breaks to the up side and down-arrows show sell signals when price breaks to the down side. The signals occur early at the beginning of major trends, but many false signals occur when price action moves sideways. A slower breakout system where n=40 would reduce false signals but signal later at the start of major trends (Schwager, 1999, pp. 234-237).

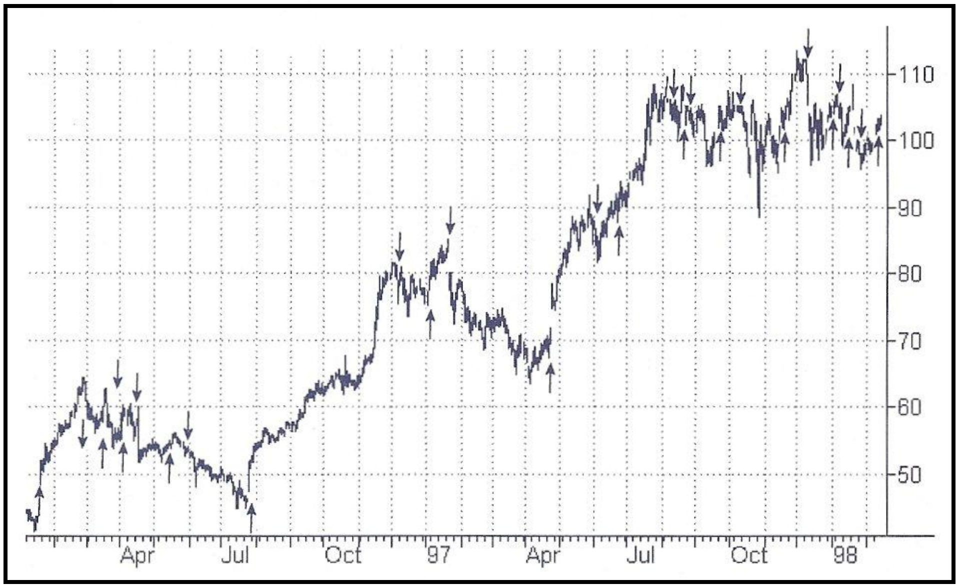


Figure 8 - IBM fast breakout system trends (Schwager, 1999, p. 235)

2.2.2.7 Stochastic

The Stochastic oscillator is based on the observation that prices usually close toward their upper range during up-trends and toward their lower range during down-trends. It is plotted on a 0 to 100 percent scale and measures where the closing price is in relation to the total price range for a certain period of time. A high reading means price is closer to the top of the range and a low reading means price is closer to the bottom of the range. The stochastic oscillator provides trading signals based on prices reaching these temporarily unsustainable overbought or oversold extremes. Stochastic comes in two versions, fast stochastic and the more popular slow stochastic, with lines called %K and %D charted on a 0 to 100 scale. Trading signals are generated when the faster %K line crosses the slower %D line in an overbought or oversold region. Usually, the overbought region is between 70 and 80, and the oversold region is between 30 and 20. Figure 9 illustrates a 14-week stochastic of Treasury Bonds. A buy signal (up-arrow) occurs when %K crosses above %D in the oversold zone (below 20), and a sell signal (down-arrow) occurs when

%K crosses below %D in the overbought zone (above 80) (Murphy, 1999, pp. 246-249; Weissman, 2005, p. 32).

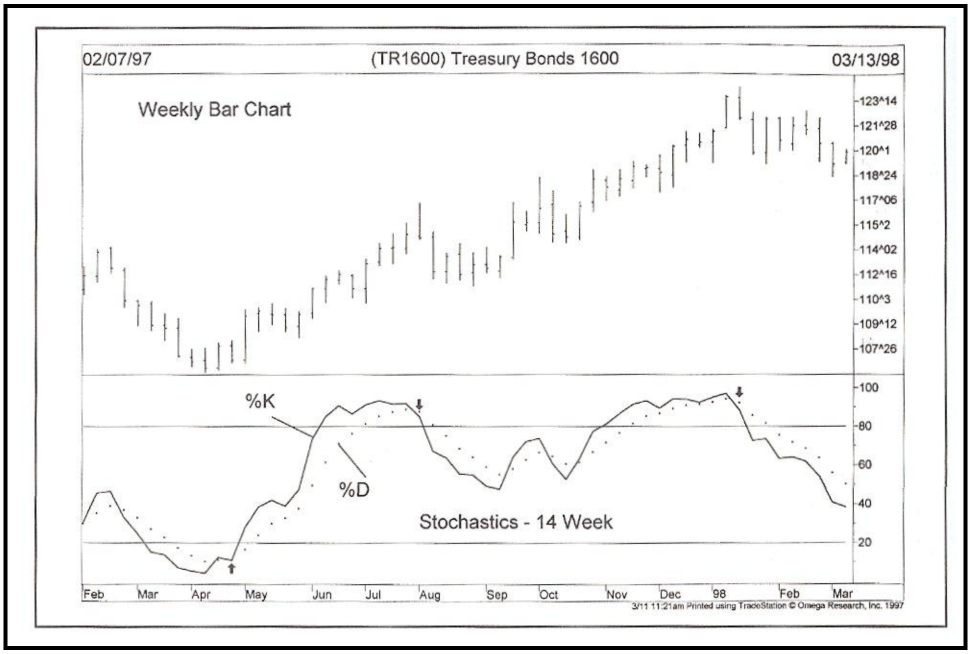


Figure 9 - Treasury bonds 1600 14-week stochastic (Murphy, 1999, p. 248)

2.2.2.8 Relative strength index

The relative strength index (RSI) is a very popular oscillator that is plotted on a 0 to 100 scale, with overbought boundary typically set at 70 and oversold boundary set at 30. A buy signal is generated when the RSI extends below the oversold boundary and then rises above that lower boundary. A sell signal is generated when the RSI extends above the overbought boundary and then falls below that upper boundary. The most popular time periods for the RSI are the 9-day and 14-day versions, although 5, 7, 21, and 28-day versions are used as well. The time period determines the amount of smoothing of the RSI line. The relative strength is calculated as: RS = (average of x-days' up closes) / (average of x-days' down closes) where x is the time period, shorter time periods resulting in more RSI volatility. The RSI is then calculated as: RSI = 100 – (100 / (1+RS)). Figure 10 illustrates a 14-day RSI for the S&P 100 Stock Index where the RSI dipping below and then rising back above the oversold level of 30 generates a buy signal. A sell signal is generated when the RSI peaks above and then drops below the overbought level of 70 (Murphy, 1999, pp. 239-246; Weissman, 2005, p. 33).

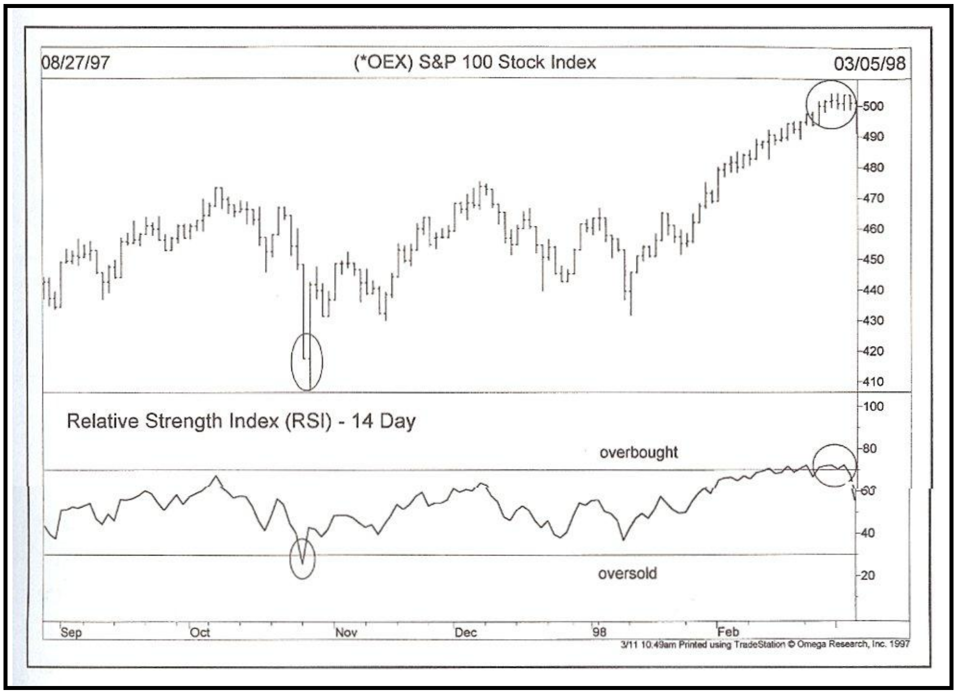


Figure 10 - S&P 100 stock index RSI (Murphy, 1999, p. 241)

2.2.2.9 Momentum and rate of change

The momentum indicator is an oscillator that subtracts price n periods ago from the current price, where 10 periods is the most common time period used. A buy signal is generated when momentum crosses above zero and a sell signal is generated when momentum crosses below zero. Except for the calculation, the rate of change (ROC) indicator is very similar to momentum, providing the same signal triggers. The ROC is calculated by dividing the current price by the price n periods ago. Figure 11 illustrates a 40-day momentum for Treasury Bonds. A buy signal occurs when the momentum crosses above the zero line and a sell signal occurs when the momentum line crosses below the zero line. The moving average can be used to confirm the momentum signals (Murphy, 1999, pp. 228-234; Weissman, 2005, pp. 34-35).

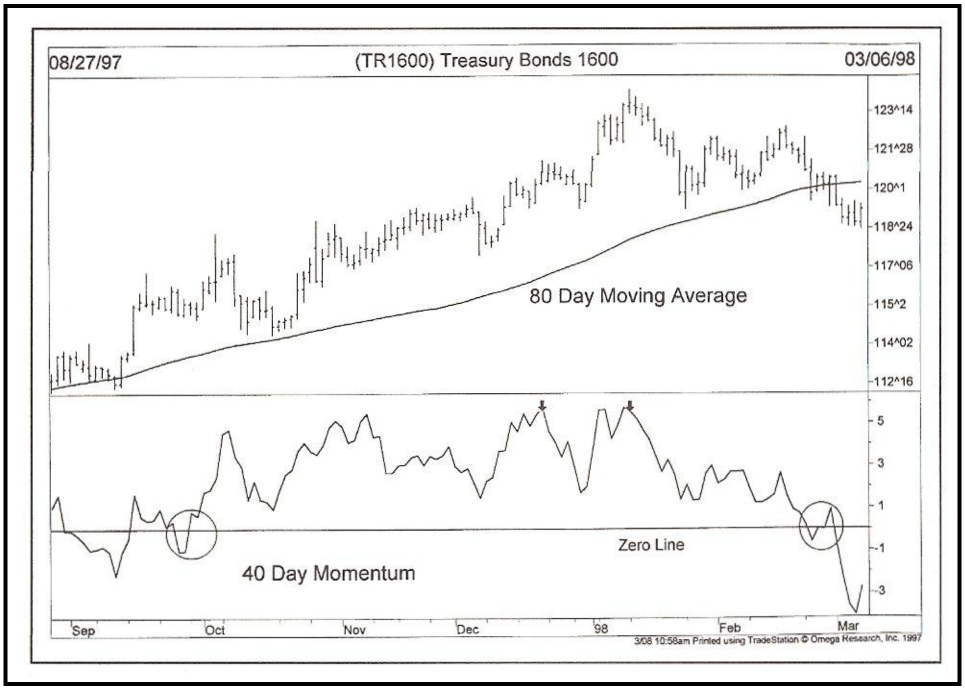


Figure 11 - Treasury bonds 40-day momentum (Murphy, 1999, p. 232)

2.2.2.10 Bollinger bands

Bollinger bands are constructed by calculating the standard deviation of price over some period of time, typically 20 time periods, and then adding and subtracting two standard deviations to a 20-period simple moving average. By using two standard deviations, 95-97% of the price data will be contained within the upper and lower price bands. Bollinger bands expand during high price volatility and can indicate that the current trend may be ending when the bands are unusually far apart. Bollinger bands contract during low price volatility and can indicate that a new trend may be starting. Price extending beyond the upper or lower band usually indicates an unsustainable extreme. When used as a counter trend indicator, price crossing above the upper band generates a sell signal and price crossing below the lower band generates a buy signal, as illustrated in the Dow industrials Bollinger bands of Figure 12. Bollinger bands work best in combination with overbought/oversold oscillators (Murphy, 1999, pp. 209-211; Weissman, 2005, pp. 36-37).

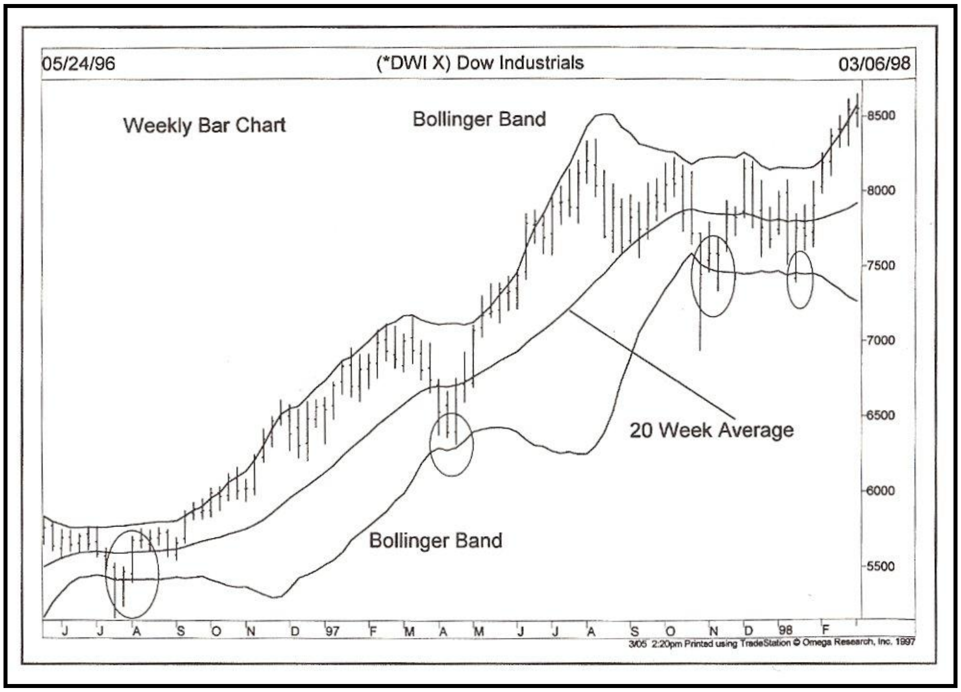


Figure 12 - Dow industrials Bollinger bands (Murphy, 1999, p. 210)

2.2.2.11 On-balance-volume

The on-balance-volume (OBV) indicator incorporates a measure of market psychology and participation in a trend by weighing price action with its volume. The OBV can confirm the quality of the current price trend by moving in the same direction as price or warn of an impending reversal by diverging from the price action. The OBV above its long-term moving average indicates an up-trend and the OBV below its long-term moving average indicates a down-trend. Figure 13 illustrates the S&P 500 Index, OBV, and their 200-day moving averages. The OBV fell below its 200-day moving average in mid-1998 as its moving average started to flatten out even though the S&P 500 Index continued to go higher. This divergence was a warning of an impending price reversal that developed about a year later (Murphy, 1999, pp. 165-166; Stridsman, 2001, pp. 229-230,263).

Figure 13 - S&P 500 index OBV (Stridsman, 2001, p.230)

2.3 Trading system development

Technical analysis can be divided into two distinct areas. Chart analysis as outlined in section 2.2.1 is subject to the visual interpretation of historical price patterns. Chart reading is largely an art, and success mostly depends on the skill of the individual chartist. Although very useful and powerful, the validity of chart interpretation cannot be objectively quantified and statistically verified, severely limiting its use as a basis for mechanical trading systems. The statistical analyst quantifies these subjective principals to incorporate them into mechanical trading systems. Mathematical technical indicators as outlined in section 2.2.2 provide objective technical analysis because the buy and sell signals they generate are based on objective and immutable rules making them well suited for mechanical trading systems by removing the subjective human element in trading (Murphy, 1999, p. 11; Weissman, 2005, p. 4).

2.3.1 Trading strategies

Many regard technical analysis as more of an art than a science. There are hundreds of technical indicators. Interpretation of signal trigger conditions can be subjective. Some indicators work better than others, consistently signaling the best times to buy and sell (Colby & Meyers, 1988, p. iii; Murphy, 1999, pp. 11, 17; Schwager, 1999, pp. 7-16).

Emotions are the cause of many common errors that traders make including overtrading, buying too early, and selling too late. A mechanical trading system can help traders avoid many common errors by eliminating emotion from trading. A mechanical trading system can be a useful tool to reduce the complexity of trading based on technical analysis by implementing a consistent trading strategy that provides signals based on technical analysis of a stock’s current trading conditions. System design should concentrate on entry and exit timing for trades. It is usually advisable to use multiple indicators in combination to provide a more balanced approach for a variety of trading conditions. Categories used to classify trading systems include trend-following and counter-trend approaches. Each has its advantages and disadvantages depending on market conditions, so a combined approach can be incorporated into a trading strategy in order to take advantage of different market conditions (Schwager, 1999, pp. 226-252).

Trend following systems typically have a lower percentage of winning trades, but the winning trades tend to be very profitable and losing trades tend to experience small losses. Since prices are range-bound more often than they trend, counter trend systems typically have a higher percentage of winning trades than trend-following systems. However, with smaller profits on winning trades and larger losses on loosing trades, their profit to loss ratios and overall performance are often inferior (Weissman, 2005, pp. 50,73).

2.3.1.1 Investment timing models

A *trading system* is made up of a set of trading rules that are used to generate trading signals and a set of parameters that can be varied to determine the timing of the trading signals. A trading rule can also include a filter, such as time delay, to provide confirmation before generating a signal. It is usually best to limit system rules and parameters to a minimum as long as it doesn’t degrade system performance (Schwager, 1999, pp. 255-256).

In order to achieve consistently good performance, an investment timing model needs an effective discipline that goes with trends and avoids significant losses. There is virtually no limit to the number of trading systems that can be devised based on a variety of source data and trading rules. A precise set of trading rules to deal with all kinds of market behavior should be developed and tested leaving no room for doubt, uncertainty, or confusion. It should tightly control investment risks while allowing maximum profits to accumulate. It must effectively handle risk and reward trade-offs in all kinds of market conditions. Although using the 200-day moving average or the 13-week momentum time frame is common, different markets have different cyclical characteristics. Using computers, market technicians can construct timing models with short-term and long-term attributes that match the cycles of the market. Testing a wide range of time frames can determine which moving average or momentum time frame is best (Colby & Meyers, 1988, pp. 4-17).

A common theme in the literature is that trend-following systems work well in trending markets and not so well in non-trending markets. Conversely, counter-trend or mean reversion systems work best in non-trending markets and not so well in trending markets. A reasonable trading approach then would be to use trend-following trading models when the market is trending and counter-trend trading models in non-trending markets, filtered by an indicator that signals whether the market is trending or not. Although results vary, directional movement index (DMI), average direction movement index (ADX), and long-term (200-day) moving averages are often cited as indicators that can provide such trending signals (Katz & McCormick, 2000, pp. 85,102-103,131; Murphy, 1999, pp. 384-387,390; Ruggiero, 1997, pp. 48,59,78-80,215,263; Stridsman, 2001, pp. 70,234,241-242,250-253; Weissman, 2005, pp. 27-29,56-58).

2.3.1.2 Trend-following strategies

Trend-following strategies typically involve some variation of moving averages or breakout models. Moving averages capitalize on the assumption that, once established, a trend will continue. The underlying concept of breakout systems is the ability of a market to move to new highs or lows indicating the potential for continuation of the trend in the direction of the breakout (Katz & McCormick, 2000, pp. 74-75; Schwager, 1999, pp. 228-234).

There are a variety of moving average calculations including simple moving averages, exponential moving averages, and front-weighted triangular moving averages. Moving averages provide a very simple means of smoothing the normal short term price fluctuations so that price trends are easier to distinguish. Moving averages work well when price is trending, but not so well when in non-trending markets where price action is choppy or moving sideways. In non-trending markets, price can cross a moving average often producing buy and sell signals in rapid succession, so the trader never knows which penetration is the one preceding either the renewal of a trend or confirmation of a reversal. A trend-following model can use moving averages to trigger a buy signal when price crosses above the moving average, and a sell signal when the price crosses below the moving average. However, moving averages always lag the corresponding transitions in price which tend to trigger signals late resulting in the early portion of new trends being missed. Shorter-term moving averages are more sensitive than longer-term moving averages. Using raw price crossing the moving average can sometimes cause spurious signals due to normal price variations, resulting in high trading costs due to frequent trading. This problem can be reduced by using two moving averages with different time periods. A buy signal is triggered when the faster moving average crosses above the slower moving average, and a sell signal is triggered when the faster moving average crosses below the slower moving average. Another approach is to use a filter that confirms the trend, such as price moving past the moving average by a certain amount, or for a certain number of time periods (Edwards & Magee, 1992, pp. 484-487; Katz & McCormick, 2000, pp. 109-131; Schwager, 1999, pp. 45-50,229-234).

The most simple trend filter is a long-term moving average, such as the 200-day moving average, where trading only in the direction of the long-term moving average significantly improves results. The directional slope method can work better in prolonged trends than the moving average crossover technique because it can reduce the number of false signals, and can use less data and more up-to-date data. When the moving average directional slope changes from one day to the next, an up move triggers a buy signal and a down move triggers a sell signal. Another moving average crossover method can trigger a buy signal when the faster moving average crosses above the slower moving average, and a sell signal is triggered when the price crosses below the faster moving average, resulting in a quicker exit. A similar technique can be applied to the directional slope method, by triggering a buy signal on the up move of the slower moving average and a sell signal on the down move of the faster moving average (Stridsman, 2001, pp. 70, 87,228).

Breakouts models trigger a buy signal when the price breaks above an upper band or threshold level, and a sell signal when the price breaks below a lower band or threshold level. The primary difference in breakout models is how the band or threshold levels are calculated. Channel breakout models can use threshold levels based on the highest highs and lowest lows for the last n-periods of data, where the value chosen for n will determine the sensitivity of the system and how fast or slow it will respond to price breakouts. Channel breakout threshold levels can also be based on price volatility, where the bands expand as volatility increases and contract when volatility decreases. Placement of the threshold levels will determine how effective a breakout model will be. The bands should be placed such that they signal a breakout into a new major trend but do not trigger false signals on normal price volatility during non-trending sideways price movement. If the bands are too wide, a breakout model will trigger a signal late and may miss a significant portion of a trend. If the bands are set too narrow, a breakout model will trigger frequent signals, resulting in higher trading costs due to a large number of trades but little profit. The look-back period used to calculate the upper and lower threshold levels can be different, which can improve the system during flat or neutral markets in times of consolidation. In order to reduce false breakout signals, a breakout model can use a trending indicator to filter breakout signals, such as the Directional Movement Index (DMI) which indicates if prices are trending or not. If prices are trending, the breakout signals are used to make trades. If prices are not trending, breakout signals are ignored (Katz & McCormick, 2000, pp. 83-108; Ruggiero, 1997, pp. 76-83; Schwager, 1999, pp. 234-237; Stridsman, 2001, p. 98).

2.3.1.3 Counter-trend strategies

Counter-trend strategies try to anticipate price by identify turning points. Oscillators are popular counter-trend indicators that fluctuate quasi-cyclically within a limited range. Oscillators provide indications of price momentum and exhaustion. Momentum refers to the rate at which price changes when price is moving strongly in one direction. Weakening trends usually have decreasing momentum which indicates a possible trend reversal. Exhaustion occurs when price becomes excessively high indicating an overbought condition or excessively low indication an oversold condition, which may precede a price reversal. A popular oscillator is the Moving Average Convergence Divergence (MACD) and MACD-Histogram (MACD-H). The MACD is computed by subtracting a longer moving average from a shorter moving average, typically exponential moving averages. The moving average of the MACD is called the signal line. The MACD-H is computed by subtracting the signal line from the MACD. A buy signal is triggered when the oscillator crosses above the signal line, and a sell signal is triggered when the oscillator crosses below the signal line. The Stochastic and Relative Strength Index (RSI) oscillators signal overbought and oversold conditions using scaled values between 0 and 100. A buy signal is triggered when the oscillator moves below the oversold threshold, and then moves back above that oversold threshold. A sell signal is triggered when the oscillator moves above the overbought threshold, and then moves back below that overbought threshold. Oscillators work best when price is in a trading range (non-trending). In order to reduce false signals during trending markets, a counter-trend model can use a trending indicator to filter signals, such as the Directional Movement Index (DMI) which indicates if prices are trending or not. If prices are trending, the counter-trend signals can be ignored. Another approach would be to use an oscillator signal as a filter, confirming trend exhaustion on price reversal (Katz & McCormick, 2000, pp. 133-152; Schwager, 1999, pp. 110-119).

2.3.1.4 Entries and exits

Transaction costs are usually accessed per trade, so total transaction costs increase proportionally with the number of trades. *Slippage* is the difference between the expected buy or sell price and the actual buy or sell price, dependant on price movement and order execution delay. Stock trading accounts commonly restrict trading until funds have settled, typically after selling stock, for a certain time period. There does not seem to be universal agreement among experts whether realistic trading practicalities such as transaction costs, slippage, and trading restrictions should be accounted for when developing trading systems. Some (Murphy, 1999, p. 498; Stridsman, 2001, p.17) suggest that trading costs should not be considered when designing and testing a trading system, the goal should be on capturing as many and as large favorable moves as possible while spending as little time in the market as possible to reduce risk. Others (Katz & McCormick, 2000, p. 89; Schwager, 1999, pp. 258-260) argue that trading costs should be accounted for because they impact profitability.

In addition to providing buy and sell timing signals, a trading model should include some provision for the method of trade entry and exit. In live trading, entry and exit orders are executed that determine the price of entry or exit. A market order is simply an order to buy or sell at the prevailing price, ensuring that the order will be filled quickly. Market orders are typically used when timing is important but may experience slippage, which can be either in favor or against a trade. A buy stop order will buy at or above the specified stop price, and a sell stop order will sell at or below the specified stop price. A buy stop order can be used as a confirmation filter to a buy signal in trend-following systems, ensuring that price is moving up before entering a trade. A sell stop order can be used to limit losses due to price moving against a trade. Slippage can be significant when prices are moving rapidly. A buy limit order will buy at or below the specified limit price and a sell limit order will sell at or above the specified limit price. A buy limit order can be used in countertrend systems to ensure entry into a trade is at a good known price without slippage. A sell limit order can be used to lock in profits when price moves above a specified price (Murphy, 1999, pp. 403-405; Katz & McCormick, 2000, pp. 71-74).

The main goals of an exit strategy are to limit losses incurred on loosing trades and maximize profits in winning trades. A money management exit or stop loss exit typically uses a sell stop order to exit the trade if price drops below a specified amount. The stop price is usually set to the maximum amount of risk that can be tolerated for that trade, but can also be set based on a threshold such as a trend line or support/resistance level. A trailing exit uses a trailing stop which adjusts up as the price moves in favor of the trade, then exists the trade when price falls below the stop price. A profit target exit usually uses a sell limit order to close a trade that has made a specific amount of profit. This exit strategy can increase the percentage of winning trades, but limits the profit per trade. A time-based exit closes a trade after a certain period of time, which indicates a trade has not moved enough to trigger another exit, and can be combined with other exit strategies. A signal exit closes a trade due to a sell signal triggered by the trading model based on its internal technical indicators and trading rules (Katz & McCormick, 2000, pp. 281-288; Ruggiero, 1997, pp. 131-132; Stridsman, 2001, p.70). The setting of sell stop orders depends on the price of the stock and its habits. Lower priced stocks need a wider stop because they tend to make larger percentage moves. Higher priced stocks tend to be less volatile, so narrower stops can be used (Edwards & Magee, 1992, p. 401).

2.3.1.5 Combining technical indicators

Technical indicators can be classified based on what type of information they provide. When developing trading models, it is usually advisable to use multiple indicators in combination to provide a more balanced approach for various trading conditions. However, it is not advisable to use multiple indicators that provide the same information as that would contribute redundant information to the model and cause other indicators to appear less important than they really are. Technical indicators can be checked for redundant information visually on charts. If they provide essentially the same trading signals, they should not be used simultaneously in a trading model. Table 1 classifies the technical indicators outlined in section 2.2.2 (Colby & Meyers, 1988, p. 36; StockCharts.com, 2010; Stridsman, 2001, p. 227).

Table 1 - Technical indicator classification (StockCharts.com, 2010)

Category	**Technical Indicator**
Trend	Moving averages
	Moving average convergence divergence (MACD)
	Directional movement indicator (DMI)
	Average directional movement index (ADX)
	Price channel breakout
Momentum	Stochastic
	Relative strength index (RSI)
	Momentum and rate of change (ROC)
	Bollinger bands
Volume	On balance volume (OBV)

2.3.1.6 Data sets

The type of historical stock data available will have an impact on which technical indicators can be used. Many indicators are based on stock price. Historical stock price data can be downloaded from the internet at the Yahoo (http://finance.yahoo.com/) or Google (http://www.google.com/finance) finance web sites, and can be retrieved in Comma Separated Values (CSV) format. The stock data includes data fields Date, Open, High, Low, Close, and Volume for each trading day over a specified period of time. Price data from Google is available in daily or weekly periods. Price data from Yahoo is available in daily, weekly, or monthly periods.

Using shorter period data usually improves trading performance as it increases sensitivity to market moves allowing quicker response to trend changes, thus increasing profitability and reward/risk ratios. Although trading activity increases, the number of trades does not increase proportionately to the increased number of data points (Colby & Meyers, 1988, p. 34).

2.3.2 Optimization

Optimization is a powerful analytical technique that systematically searches for the indicator formula that produces the highest or most consistent profit over some historical time period. Although optimizing a trading strategy over past data does not guarantee that the strategy will perform the same in future trading, there is enough similarity to make optimization worthwhile since market behavior and price patterns do not change much over time, particularly the longer term trends (Colby & Meyers, 1988, pp. 4,18).

A trading model consists of parameters and rules that signal when to buy and sell. Optimizing a trading model involves finding the best possible set of trading rules and parameters. The performance of each combination of trading rules and parameters can be evaluated using a fitness function, which calculates a value that represents model performance. The calculation of the fitness function can be calculated in any manner desired based on trading style, risk tolerance, or other trader preferences. Common methods include maximizing profits, and may account for other performance metrics such as drawdown, percent winning trades, or profit to maximum drawdown ratio. An optimization process searches for the best combination of trading rules and parameters that result in the greatest fitness value as calculated by the fitness function (Katz & McCormick, 2000, pp. 29-30; Weissman, 2005, p. 127).

Brute force optimization is conceptually simple and effective, and is relatively easy to implement. A brute force optimizer systematically evaluates every possible combination of rules and parameters, so it will always find the best possible combination. However, brute force optimization can become very slow as the number of combinations grows. Therefore, it is a good choice for small systems that optimize a relatively small number of combinations that can be evaluated in a reasonable period of time (Katz & McCormick, 2000, pp. 32-34).

User-guided optimization evaluates selected combinations of rules and parameters, guided by an intelligent user. Brute force style partial optimizations are performed only on selected combinations. This might involve a variety of methods including evaluation of all combinations in a selected range of rules and parameters, evaluating only selected rules or parameters, or perhaps evaluating parameters through a range of values using course increments. The partial optimization process can be repeated as many times as desired. One of the benefits of user-guided optimization is that a skilled user may be able to perform an optimization much faster than brute force optimization by focusing on areas that have the most potential and avoiding areas that are unlikely to produce good results. User-guided optimization is a good choice for making minor adjustments to existing systems, or for evaluating sensitivity to rule or parameter changes (Katz & McCormick, 2000, pp. 34-35).

Genetic optimization simulates the evolutionary processes of random selection and recombination. Genetic optimizers are good at finding the best solution and work well with complex fitness functions. Genetic optimizers are very efficient even when processing a large number of rule and parameter combinations. They can be orders of magnitude faster than brute force optimizers. Like user-guided optimization, genetic optimization focuses only on the important areas but does not need to be guided by an intelligent user. Genetic optimizers are among the most powerful and are the optimizers of choice when there are many rule and parameter combinations or a complex fitness function (Katz & McCormick, 2000, pp. 35-38,257-280).

With today's computer technology, alternative optimization techniques such as walk-forward optimization and self-adaptive systems are practical. These systems are optimized on recent data, then used for live trading for some period of time, then optimized again. This cycle is repeated indefinitely, resulting in a system that is always optimized using recent data, and live trading always occurs on out-of-sample data. Self-adaptive systems automate the technique by optimizing on fixed intervals or some other criteria (Katz & McCormick, 2000, pp. 45-46).

In order to avoid data curve fitting, a trading model should be optimized over a large representative sample data set to include all types of market environments such as bullish, bearish, trending, and non-trending. If the sample data set is too small, it is less likely to be representative of the data in other data sets. Optimization on a small data set may find the best set of rules and parameters for that data set, but is likely to perform poorly on other data sets as well as in live trading. To be representative, the sample data set used for optimization should be as recent as possible so that it reflects current patterns of market behavior, including up trending and down trending cycles. In order to eliminate performance bias, the data should include an integer multiple of a full low frequency cycle. For example, given the well-known 4-year stock market cycle, the data set should include at least 8 years of data (twice the cycle length).

Optimization should result in a minimum of thirty trades taken, to confirm that the results are not by chance of just a few trades (Colby & Meyers, 1988, p. 36; Katz & McCormick, 2000, pp. 41-44; Weissman, 2005, p. 124).

Parameter curve fitting can result from an excessive number of variable parameters and rules, and as with small sample data sets can impact optimization by working well on in-sample data but perform poorly on out-of-sample data and live trading. Therefore, trading models should limit the number of variable parameters and rules to no more than two to five, especially for small data samples. For a given data sample size, the fewer parameters and rules to optimize, the more likely the model will be able to filter out randomness and maintain its performance in out-of-sample tests and live trading. For a sample data set of only a few years of end-of-day data, even two or three parameters may be excessive (Colby & Meyers, 1988, p. 36; Katz & McCormick, 2000, pp. 43-45; Weissman, 2005, pp. 124-125).

2.3.3 Testing, evaluation, & analysis

One of the primary benefits of a mechanical trading system is that it provides a means to back-test, or paper-trade, a trading model without risking real money. Simulations can test the trading model using user-defined trading rules over historical data to gain insight as to how well it might perform when applied to live trading (Katz & McCormick, 2000, p. 13).

After a trading model has been optimized on historical in-sample data, it is essential that it be tested using blind simulation or ex-ante cross validation on a more recent out-of-sample data set to verify that it consistently maintains its performance results. This critical step will provide confidence in the trading model before committing it to live trading with real money. If performance results vary significantly (e.g. excessive drawdown) from in-sample tests, the parameter set for the trading model should be discarded. Additional verification can be done by calculating inferential statistics on both in-sample and out-of-sample tests. These statistics will indicate the probability that the trading model will maintain its performance in other data samples and in live trading (Colby & Meyers, 1988, pp. 18-19; Katz & McCormick, 2000, pp. 43-45; Weissman, 2005, pp. 148-150).

Some objective standard of comparison is needed in order to judge the effectiveness of a technical indicator. The passive buy-and-hold strategy is often used as a performance comparison, but is not really a good choice since it is dependent on the time period. Almost any timing tool can outperform buy-and-hold in down markets and most timing tools cannot keep pace with buy-and-hold in very strong bull markets. A good standard of comparison is the 40-week simple moving average, where a buy signal occurs when price closes above its 40-week simple moving average and a sell signal occurs when price closes below its 40-week simple moving average (Colby & Meyers, 1988, pp. 40-41).

Total profits and maximum equity drawdown are vital measurements of the workability of a trading model. A model that sustains very large drawdown is not practical even if total profits are high. A key performance metric is the reward/risk ratio, the ratio of total profit to maximum equity drawdown (Colby & Meyers, 1988, p. 17). Other data collected that can be used to evaluate system robustness include total net profit, number of trades, number of days (average trade duration), maximum drawdown amount (maximum peak-to-valley equity drawdown), maximum drawdown duration, maximum consecutive losses, profit to maximum drawdown ratio (higher is better), average profit to average loss ratio (higher is better), percentage winning trades, and percentage time invested (smaller is better) (Weissman, 2005, pp. 49-50).

The system should generate output data that can be used to evaluate the trading model performance, such as gross and net profit, number of winning and losing trades, and maximum drawdown. The system should also provide a detailed trade-by-trade report, to allow analysis of the model's trading style. The trade-by-trade data should include trade entry and exit dates, prices, quantity, profit or loss per trade, and cumulative profit or loss. Data output should be formatted so that it can easily be imported into a spreadsheet or other application that supports statistical analysis, and allow comparison between simulations of different trading models. Spreadsheets provide a convenient way of sorting and displaying data, and creating graphs and histograms (Katz & McCormick, 2000, pp. 15-22).

Evaluating the reliability and stability of a trading system requires a statistical analysis of system performance over live trading and historical test periods. Data should be collected and analyzed for the total time period of each data set tested and for a moving window of those periods. Similar statistical traits of the collected data over different time periods would indicate a robust system and increase confidence that the system would continue to work in the future. The equity curve should be analyzed to ensure that it is stable and upward sloping. The one year moving window of equity should be above zero at least seventy percent of the time. When live trading, two sets of data should be collected. One set should be based on simulated trading and one set based on actual trading results. Comparing the difference between the two data sets can reveal valuable information that can be used to improve the system, such as adjusting risk tolerance, or more accurately estimating slippage (Ruggiero, 1997, pp. 225-237).

The integrity of the system should be verified by reviewing the performance data and by spot checking the list of trades. Review of performance data should look for anomalies that might indicate a potential system programming error, such as all buy or all sell signals, all winning or all loosing trades, or average length of trades atypically long or short. Spot checking involves checking trades to verify entry and exit conditions were met, trades were taken at the correct price, and commissions and slippage were accounted for correctly (Weissman, 2005, p. 121).

2.4 Fuzzy logic

Fuzzy logic attempts to combine the imprecision associated with events and objects to produce intelligent reasoning systems. It is concerned with the imprecision associated with describing events or objects, and the uncertainty or vagueness inherent in how they are characterized. Fuzzy set theory defines how fuzzy sets are organized and the operations allowed on them. A fuzzy logic system makes logical inferences from a collection of fuzzy sets (Cox, 1995, pp. 63,532-533; Cox, 1999, pp. 6-7).

2.4.1 Fuzzy sets

Fuzzy sets provide a way to represent how well objects satisfy vague descriptions. An example of this might occur when describing whether a 5'10" person, Nate, is tall. It's not a question of uncertainty about his height, but that the linguistic term tall does not refer to a clearly demarked true or false value. You might say that Nate is sort-of tall. Fuzzy set theory allows for a definition that defines degrees of tallness, treating tall as a fuzzy predicate where the truth value tall(Nate) is represented by a number between 0 and 1 (Russell & Norvig, 2003, p. 526).

The notation $\mu A(x)$ denotes the degree of membership value x has with linguistic value A. There are no clear boundaries between one linguistic value and another. For example, there is a fuzzy boundary between a person of average height and a tall person, as there is some overlap of their values within a continuous scale. Even though there may not be universally defined boundaries between linguistic values, a person 7’ tall would definitely not be considered average height. Linguistic values are context dependent; their range of values depends on the variable they are associated with. For example, the range of values for tall would be quite different when describing a building verses a person. In order to be mapped into a fuzzy set, a measured (crisp) value must be converted using a fuzzy membership function. Each linguistic variable value has a membership function, and the result of the function is a degree of membership on a 0 to 1 scale, which is the strength of association that the measured (crisp) value has with a linguistic value. For example, a person 6' in height might be associated with both average and tall, but more strongly associated with tall (Callan, 2003, pp. 154-155).

Figure 14 illustrates three membership functions for water temperature over a range of 0-100 °C using the linguistic values cold, warm, and hot. Where the functions overlap, there is a fuzzy boundary where the temperature in that area maps to membership within both linguistic values. In the example shown, a temperature of 80 °C would be warm with 0.2 degree of membership and hot with 0.5 degree of membership. The shape of membership functions depend on the context of the application, and can be constructed using a number of different shapes including triangular, normal distribution, and S-shaped, among others (Callan, 2003, pp. 155-157).

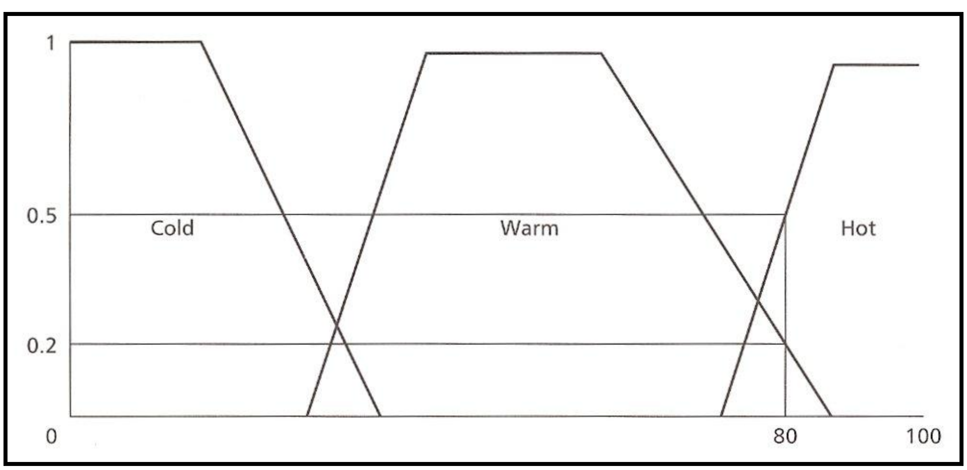


Figure 14 - Water temperature membership functions (Callan, 2003, p.157)

2.4.2 Fuzzy systems

Fuzzy set theory supports the more general theory of fuzzy logic, which supports the logical constructs used to create and manipulate fuzzy systems, also known as fuzzy or approximate reasoning, as shown in Figure 15. In fuzzy or approximate reasoning systems, knowledge is encoded using fuzzy rules and heuristics in order to deal with imprecise or ambiguous information. As all rules are evaluated, each rule contributes to resolution of its output variable, and the resulting fuzzy sets representing each output variable are combined to find an expected value (Cox, 1995, pp. 63,532-533; Cox, 1999, pp. 6-7).

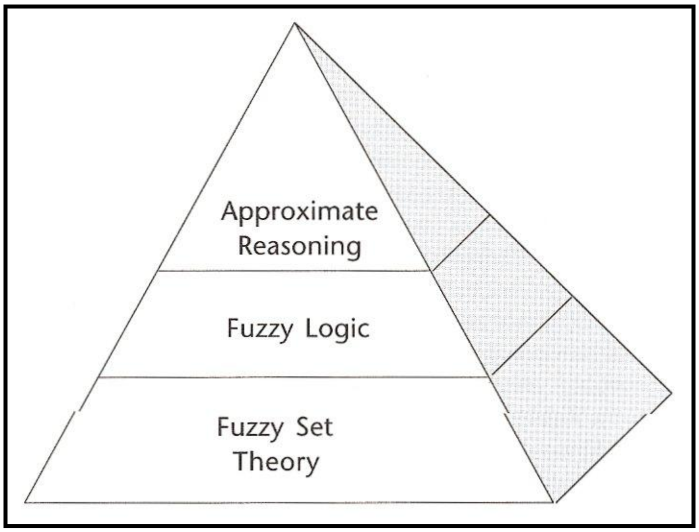


Figure 15 - Levels of logic supporting approximate reasoning (Cox, 1999, p. 7)

Fuzzy inference systems involve three stages of processing. The first stage, fuzzification, converts measured crisp input values into linguistic fuzzy variable values. Inference rules of the form "IF … THEN" process the input fuzzy variables to produce output fuzzy variables. Defuzzification then combines the output fuzzy variables and converts them into a precise crisp value (Callan, 2003, p. 157).

The rule antecedent (the IF part) relates to the inputs. It joins variables using fuzzy set operators such as AND and OR operators. Applying the AND operator results in the minimum degree of membership of two linguistic variables. Applying the OR operator results in the maximum degree of membership of two linguistic variables. For example, if Nate has degree of membership 0.35 in the tall fuzzy set and 0.75 in the young fuzzy set, “height=tall AND age=young” would evaluate to a value of 0.35, and “height=tall OR age=young” would evaluate to a value of 0.75 (Callan, 2003, pp. 158-159).

The rule conclusion (the THEN part) relates to the outputs. Each rule implies a degree of support for its conclusion. Typically, all rules are evaluated and their implied effects combined to produce a single crisp output value. For example, assume a car cruise controller that makes throttle adjustments based on measured speed error and acceleration inputs has fuzzy set input functions and throttle output function as defined in Figure 16 and has a measured speed error of 0 and an acceleration of 8 when the following two rules fire:

1) IF Speed Error=Zero AND Acceleration= Zero THEN throttle=C (constant)
2) IF Speed Error = Zero AND Acceleration =Positive THEN throttle=RS (reduce small amount)

From the Speed Error functions, “Speed Error=Zero” results in a degree of membership 1.0. From the Acceleration functions, “Acceleration= Zero” results in a degree of membership 0.2, and “Acceleration =Positive” results in a degree of membership 0.6. Thus, support for the conclusions from the two rules is as follows:

1) Membership of C is min(1.0,0.2)=0.2
2) Membership of RS is min(1.0,0.6)=0.6

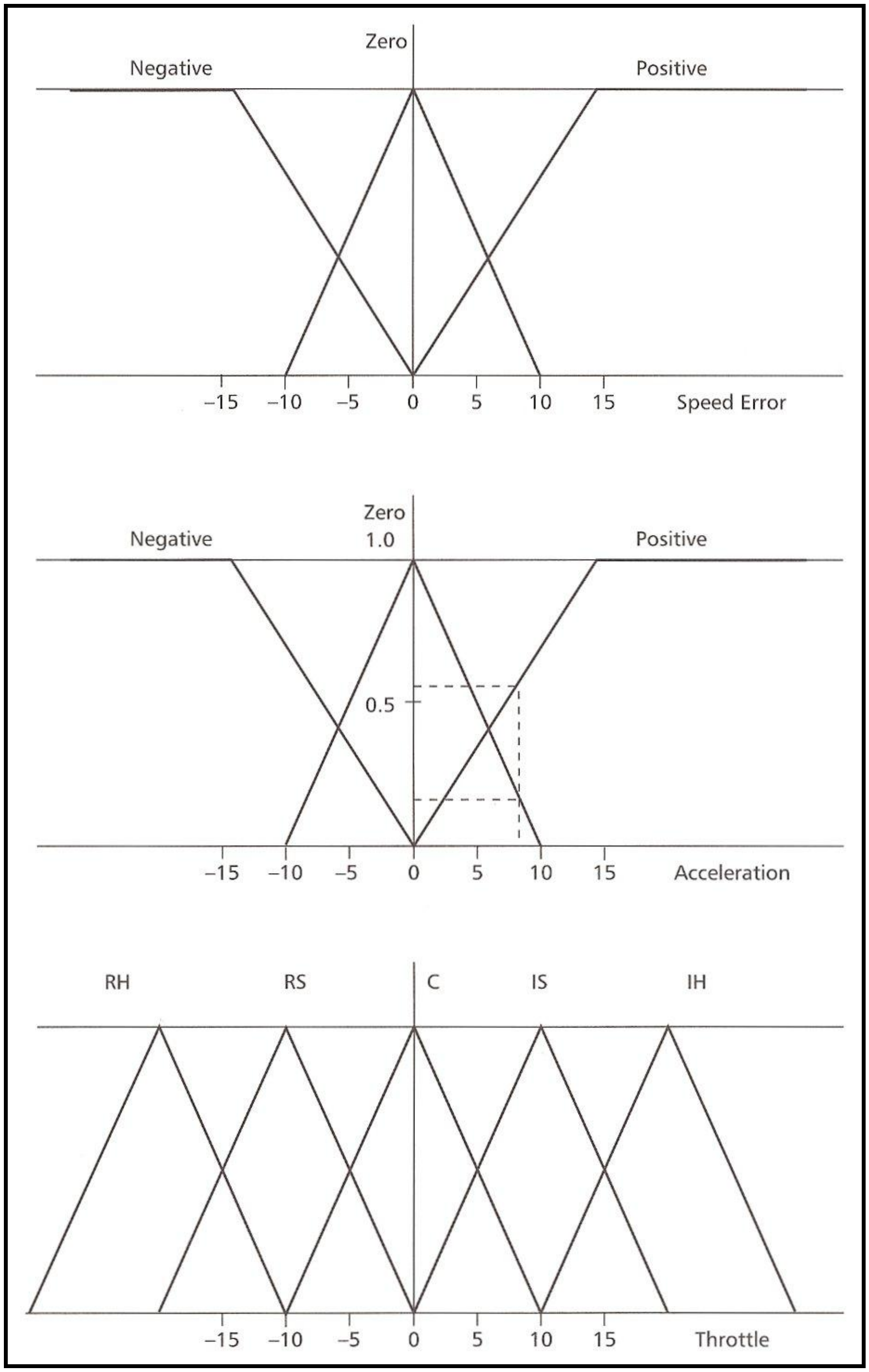


Figure 16 - Car cruise controller fuzzy functions (Callan, 2003, p.161)

The outputs must be combined to produce a single crisp throttle adjustment value. A popular defuzzification method is to find the center of gravity. Figure 17 shows the two output membership functions, cut off at the height corresponding to their output degree of membership.

The area under each function represents the strength of each conclusion, and the center of gravity of these combined areas result in the crisp output value. In this example, the center of gravity calculation results in a throttle adjustment value of -7 in response to the input values speed error of 0 and acceleration of 8 (Callan, 2003, pp. 159-163).

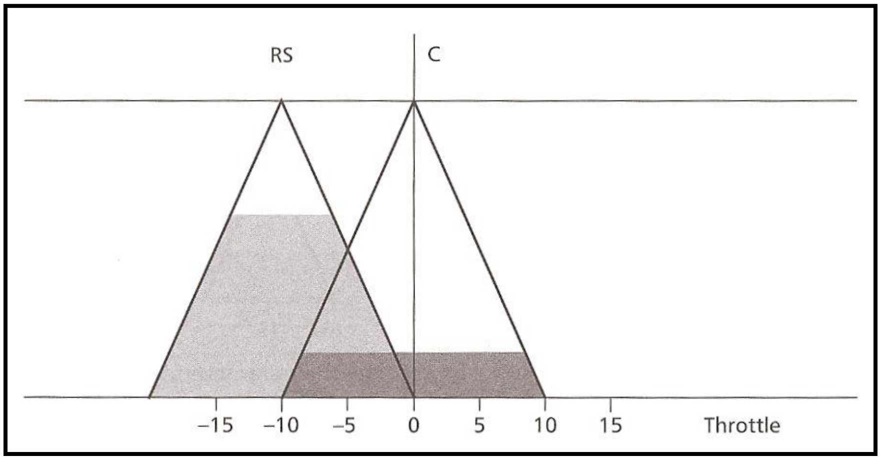


Figure 17 - Car cruise controller fuzzy output functions (Callan, 2003, p.162)

In some applications, a resulting output linguistic value is sufficient when it is used to provide a verbal or qualitative answer. In other applications, defuzzification is required because the output must be a crisp numeric value (VonAltrock, 1997, p. 42), such as in the car cruise controller example.

In addition to the min-max method of inference in fuzzy systems, used in the car cruise controller example, decision models can solve many problems by using the fuzzy additive method where all rules make some contribution to the output (Cox, 1999, pp. 284-303). The simple combination of fuzzy logic inference principles also can be extended by applying a weighting factor to each rule, corresponding to its importance relative to other rules (VonAltrock, 1997, p. 42).

The center-of-maximum defuzzification method is commonly used in fuzzy logic applications, although other defuzzification methods are more accurate for some applications such as the center-of-gravity (also called center-of-area or centroid) defuzzification method used in the car cruise controller example. To select the proper defuzzification method requires an understanding of the linguistic meanings that underlies the defuzzification process, best compromise and most plausible result. The center-of-maximum method determines the most typical value for each term and then calculates the best compromise of the result. The mean-of-maximum method produces the most plausible result; it selects the typical value of the term that is most valid rather than balancing out the different inference results. The center-of-gravity method finds the balance point by calculating the weighted mean of the fuzzy outputs. Continuity is an important property of defuzzification methods, where small changes in an input value cannot cause an abrupt change in an output value. Table 2 provides a comparison of the defuzzification methods discussed. In decision support systems, the center-of-maximum method is commonly used for quantitative decisions and the mean-of-maximum method is often used for qualitative decisions. The mean-of-maximum method is also typically used in pattern recognition applications (Cox, 1999, pp. 303-328; VonAltrock, 1997, pp. 356-363).

Table 2 - Comparison of defuzzification methods (VonAltrock, 1997, p. 363)

	Center-of-Area (CoA, CoG)	**Center-of-Maximum (CoM)**	**Mean-of-Maximum (MoM)**
Linguistic Characteristic	Best Compromise	Best Compromise	Most Plausible Solution
Fit with Intuition	Implausible with varying MBF shapes and strong overlap of MBFs	Good	Good
Continuity	Yes	Yes	No
Computational Efficiency	Very Low	High	Very High
Applications	Control, Decision Support, Data Analysis	Control, Decision Support Data Analysis	Pattern Recognition, Decision Support,

As shown in Figure 18 (VonAltrock, 1997, pp. 327-332), most practical fuzzy logic linguistic variable implementations use standard membership functions (Standard-MBFs) of linear or spline shape. Input variables may use any of the Standard-MBFs; however most applications only use the Lambda-Type membership functions for output variables. The Standard-MBFs have a number of advantages:

- They are simple, yet accurate enough to represent most decision systems.
- They are easy to interpret.
- Implementation is computationally very efficient.

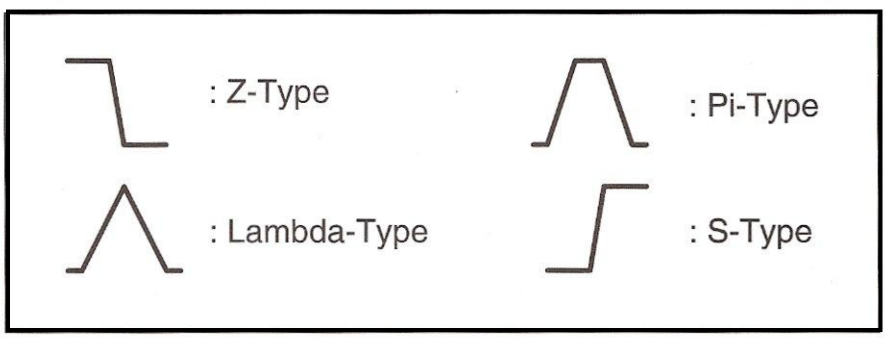


Figure 18 - Standard membership functions (VonAltrock, 1997, p. 327)

Fuzzy set hedges (Cox, 1999, pp. 217-251) play the same role in fuzzy rules that adjectives and adverbs play in English sentences by modifying the shape of fuzzy set membership functions. As shown in Table 3, there are several classes of hedge operators; those that intensify the membership function (very, extremely), that dilute the membership function (somewhat, rather), that form a complement function (not), and that approximate a fuzzy region or convert a scalar to a fuzzy set (about, near, close to, approximately).

Table 3 - Fuzzy linguistic hedges and their approximate meanings (Cox, 1999, p. 218)

HEDGE	**MEANING**
about, around, near, roughly	Approximate a scalar
above, more than	Restrict a fuzzy region
almost, definitely, positively	Contrast intensification
below, less than	Restrict a fuzzy region
vicinity of	Approximate broadly
generally, usually	Contrast diffusion
neighboring, close to	Approximate narrowly
not	Negate or complement
quite, rather, somewhat	Dilute a fuzzy region
very, extremely	Intensify a fuzzy region

The dynamic transformation of a membership function is calculated to approximate the desired linguistic characteristics. For example, the hedge very can intensify a membership function by squaring it, as illustrated in Figure 19, where a person 5 ½ feet tall would have a degree of membership 0.56 on the original Tall function, but only 0.28 on the hedged very Tall function. A person would have to be much taller, over 6 feet, in order to have of membership 0.56 on the very Tall function.

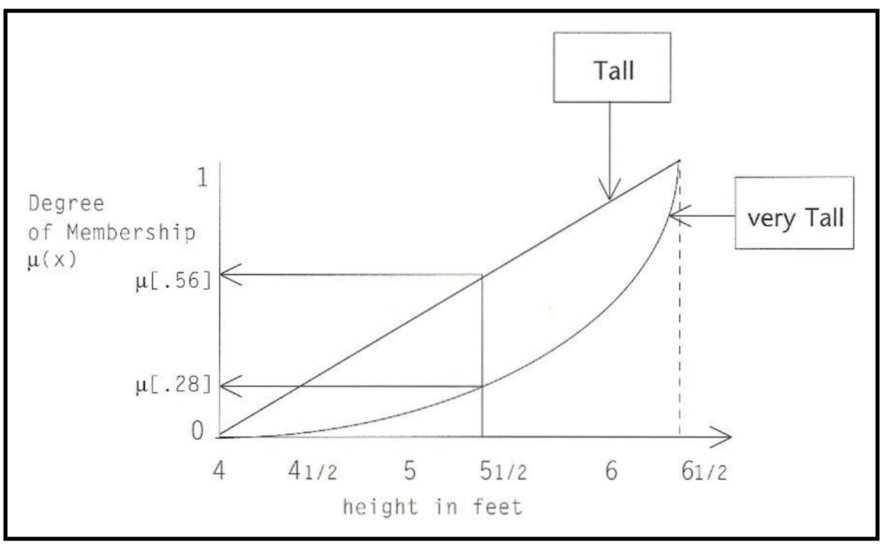


Figure 19 - Comparing Tall and very Tall at 5 ½ feet (Cox, 1999, p. 233)

2.4.3 Fuzzy applications

Fuzzy logic has been used in many control engineering applications. It has been used to control subway cars, camera and camcorder autofocus and anti-jitter mechanisms, auto braking systems, transmission controls, and fuel injectors (Rao & Rao, 1993, p. 29). In an application traditionally implemented with a conventional proportional-integral-derivative (PID) controller, Cox (1999, pp. 418-428) illustrated a steam turbine fuzzy logic controller that adjusts a fuel injector nozzle based on temperature and pressure in a steam containment vessel. Traditionally PID implementations are based on mathematical process models whereas fuzzy controllers (see Figure 20) use heuristics encoded in knowledge-based rules.

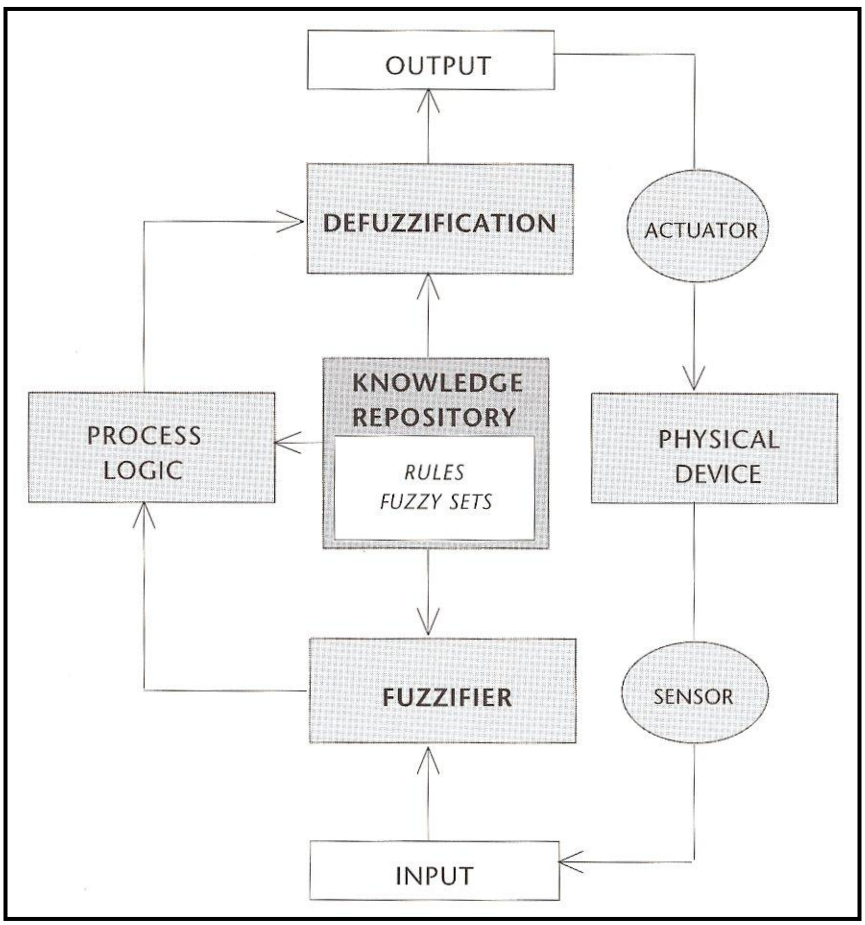


Figure 20 - Fuzzy logic controller (Cox, 1999, p. 419)

Cox (1995, pp. 40-42,295-308; 1999, pp. 43,428-474) illustrated how fuzzy logic approximate reasoning can be used in decision support using a new product pricing model (see Figure 21) developed for a British retail firm in the mid-1980s. Many imprecise and uncertain factors are involved in pricing new products such as estimated product demand, competitor pricing, market price sensitivity, manufacturing costs, spoilage, seasonality, product life cycle, time to market, product uniqueness, and window of opportunity. This example illustrates the ability of fuzzy systems to deal with multiple constraints and to model cooperating, collaborating, and conflicting knowledge from multiple experts in different fields such as finance, sales and marketing, manufacturing, transportation, and administration.

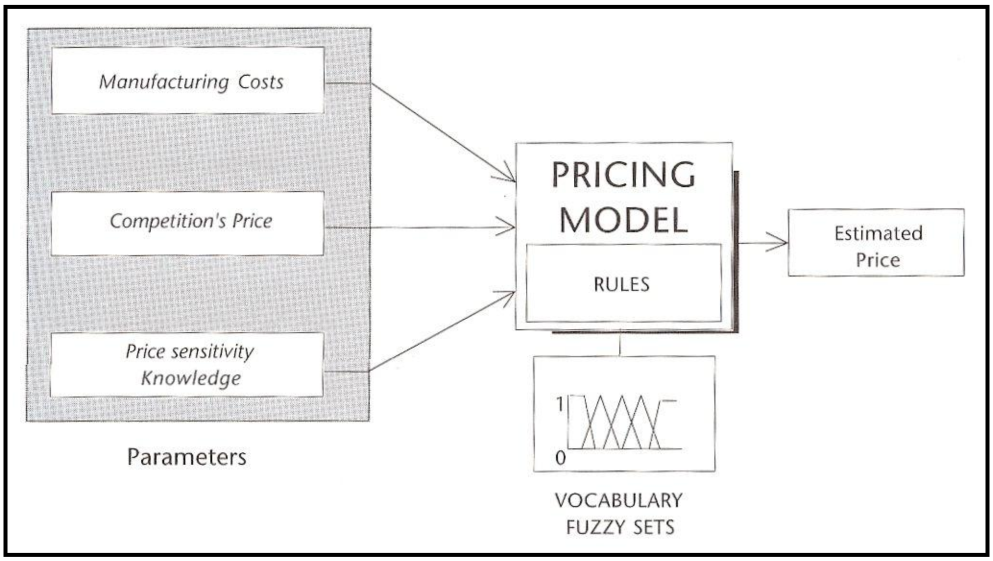


Figure 21 - New product pricing model (Cox, 1999, p. 430)

VonAltrock (1997, pp. 263-323) developed a number of case studies to show the uses and benefits of fuzzy logic applications in business, finance, and data analysis using the fuzzyTECH for Business software application.

Cox (1995, pp. 145-215) illustrated how fuzzy logic can be applied to database queries by using fuzzy linguistic values in the WHERE clause of an SQL query to more closely match the intended meaning. For example, “SELECT COMPANY, REVENUES FROM MFGDBMS

WHERE REVENUES > 600" might be stated using the fuzzy query "SELECT COMPANY, REVENUES FROM MFGDBMS WHERE REVENUES are HIGH". A fuzzy set that defines how to map REVENUES to HIGH would allow the query to return companies with high revenues, sorted by how well each maps to the fuzzy set.

Fuzzy logic has been used in data mining applications, such as the Environmental Scenario Search Engine, for querying and mining large environmental data archives, which allows a user to query the data in meaningful human linguistic terms. For example, a user might request an example of an atmospheric front near Moscow (with satellite images), how often such fronts occur, and if they have been increasing in the last 10 years (Zhizhin, Poyda, Mishin, Medvedev, Kihn, & Lutsarev, 2006).

Knowledge mining and rule discovery methods have been developed to discover relationships from data sets, such as large databases, in order to create the fuzzy sets and rules of fuzzy systems that reflect the system behavior within the domain of these sets (Castellano, Fanelli, & Mencar, 2003; Cox, 1995, pp. 217-242).

Popoola, Ahmad, & Ahmad (2004) developed a method for modeling a noisy time series using wavelet analysis and fuzzy logic. The method used high- and low-pass filters to divide the original time series into separate frequency components. The highest frequency (noisy) components were discarded and fuzzy logic models build for the remaining wavelet components. The fuzzy models provide single step prediction for each component, and when recombined provide an aggregate prediction model for the time series. Experiments revealed that the fuzzy-wavelet model outperformed other models tested.

Rao & Rao (1993, pp. 30-31) illustrated how fuzzy logic can be used with a neural network by using a fuzzifier function to pre-process data for the neural network, as shown in Figure 22.

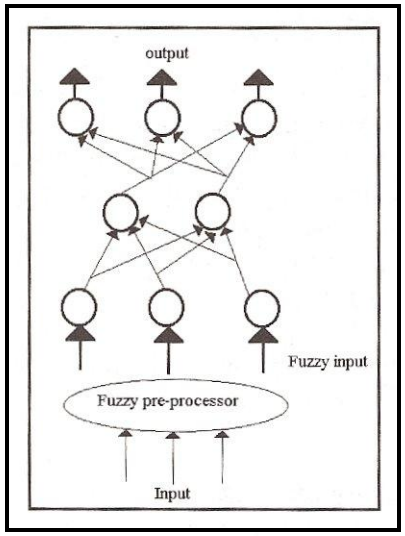


Figure 22 - Neural network with fuzzy pre-processor (Rao & Rao, 1993, p. 30)

They illustrated this concept with an example application to predict the direction of the stock market based in part on fiscal policy of the Federal Reserve. As shown in Figure 23, fiscal policy can be described using fuzzy categories ranging from very accommodative to very tight, based on the discount rate. For example, a discount rate value of 8% maps to a tight value of 0.8 and an accommodative value of 0.3. These values are normalized to a percentage probability by dividing each by the total, so the probability of the value being tight is 0.8/1.1=.73 and the probability of the value being accommodative is 0.3/1.1=.27.

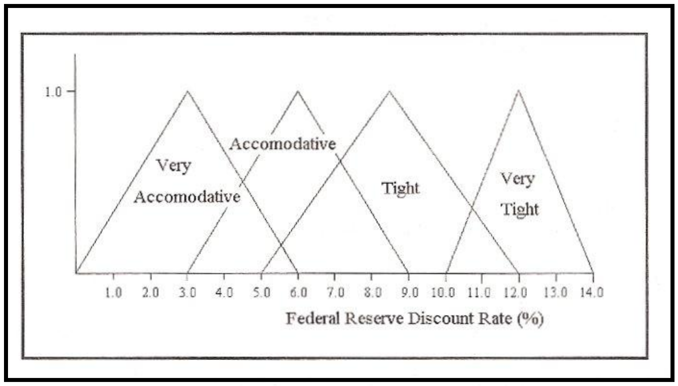


Figure 23 - Fuzzy categories for Federal Reserve policy based on discount rate (Rao & Rao, 1993, p. 31)

2.5 Fuzzy logic trading

The following provides a brief review of how fuzzy logic has been used in trading systems, highlighting various techniques of how common technical indicators are incorporated into fuzzy systems, including optimization and evaluation. The research shows that fuzzy logic trading systems based on technical analysis have successfully been developed to provide useful trading tools.

Ahmad, Gayar, & Elazim (2006) developed a fuzzy logic trading model based on technical indicators Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), and Stochastic Oscillator. Input variables were mapped to linguistic values for MACD as Positive, Zeros, Negative, RSI as High, Medium, Low, and Stochastic as Upcross, Zerocross, Downcross using trapezoid and triangular membership functions. The output variable Action was mapped to linguistic values Overbought, Hold, and Oversold using Gaussian membership functions. Eleven fuzzy rules were developed of the form “If RSI is Low and MACD is Positive and Stochastic is Upcross then Overbought”. The center-of-area method was used for defuzzification, to determine the crisp output value, which was then compared to minimum threshold MIN_T and maximum threshold MAX_T values to trigger BUY or SELL signals. These threshold values were dynamically determined base on stock price trend, up, down, or sideways using a Threshold Fuzzy Model, although they did not provide details. Tests on the Dow30 Index were performed over select uptrend, downtrend, and sideways markets using the fuzzy logic trading model and multiple benchmark models based on traditional technical indicators. Results were evaluated using six different performance parameters and showed that the fuzzy model outperformed all benchmark models in downtrend and sideways markets, also performing very well in the uptrend market test.

Cheung & Kaymak (2007) developed a fuzzy logic based trading system that used the Commodity Channel Index (CCI), Relative Strength Index (RSI), Moving Average Convergence and Divergence (MACD) and the Bollinger Bands technical indicators, where each indicator used a fixed set of parameter values. For example, the look-back period for RSI was 20 weeks. The calculated technical indicator values were mapped into seventeen input fuzzy variables. Some indicators lead to multiple fuzzy inputs. For example, the RSI provided three values, the distance to the upper bound, the distance to the lower bound and the distance to the middle line. The fuzzy output trading signal was mapped to linguistic values Strong Sell, Sell, Buy, and Strong Buy. Defuzzification of the output used the largest of the maximum (LOM) method where the output with the largest membership was selected. All input and output membership functions were Gaussian. Twelve fuzzy rules were defined, each using two technical indicators, of the form “IF $MACD_f$ is low and $RSI_{upper(t)}$ is low and $RSI_{upper(t-1)}$ is high THEN SELL”. The input and output parameters of the membership functions were optimized using genetic algorithms, as they are superior to other approaches such as neural networks by providing search efficiency and global optimization, and allow more flexible fitness functions. The fitness function was defined as the average return of trades over a number of sliding windows within the in-sample data set. Five historical data sets within a ten year period were used, where within each data set 90% was used for in-sample training and 10% was used for out-of-sample testing. Performance of the system was evaluated in comparison to benchmark buy-and-hold strategies and experts of a financial institution using a proprietary trading system. The Sharpe ratio, which measures the average return per unit risk, was used as the measure of overall performance over the out-of-sample period. The fuzzy system outperformed the benchmarks in four of the five out-of-sample testing periods.

Doeksen, Abraham, Thomas, & Paprzycki (2005) looked at stock trading with soft computing models using neural networks, fuzzy inference systems, and genetic algorithms. The systems were developed and testing for Intel and Microsoft stock using historical data from 1997 to 2003. Almost all systems significantly outperformed the buy-and-hold strategy. It is interesting to note that the systems developed for Microsoft significantly outperformed the systems developed for Intel, which suggests that selecting the right stock may be just as important as developing the best system.

Dourra & Siy (2002) examined a fuzzy logic system based on the Rate of Change (ROC) momentum indicator, the stochastic momentum indicator, and the Bollinger Bands indicator, each using a 30 day look-back period. From these indicators, seven fuzzy input variables were defined and mapped to linguistic values low, medium, big, and large using bell shaped membership functions. Based on indicator buy and sell trigger conditions, a set of fuzzy rules were defined that used the fuzzy input variables to produce a fuzzy output that was also mapped to linguistic values low, medium, big, and large on a bell shaped membership function. The fuzzy output was then converted to a crisp value using the center-of-area defuzzification method. The crisp output value was then compared to an upper trigger level (UTL) to generate a BUY signal and a lower trigger level (LTL) to generate a SELL signal. Two trading strategies were defined, the first dynamically adjusted trigger levels based on system performance, and the second used constant trigger levels based on risk tolerance. Testing on four stocks showed that over a three year period the fuzzy system results were excellent, substantially outperforming the S&P 500.

Gamil, El-fouly, & Darwish (2007) developed a fuzzy logic trading model using moving averages (MA), for various moving average time frames (10, 20, 50, 70, 100, and 200 day). They constructed input fuzzy variables of normalized moving averages (NMA) where NMA = (Price – MA) / Price. They created membership functions to map the NMA crisp values to linguistic values Low, Normal, and High. The output trade decision was mapped to linguistic values Buy, Sell, or Hold. Fuzzy rules were of the form “If NMA is High then Decision is Buy”. Genetic algorithms were used to tune the fuzzy rules for the trading model over a one year period. The system was then tested using a number of sample stocks over subsequent short-term (1 or 2 day), medium-term (1 week), and long-term (2 week) periods to assess the model’s trade decision accuracy in predicting future price movement. Successful prediction was 100% for short-term tests, 90% for medium-term tests, and 80% for long-term tests.

Ghandar, Michalewicz, Schmidt, To, & Zurbrugg (2009) developed a fuzzy logic based trading system that dynamically adjusted trading rules based on market conditions. Using their evolutionary algorithm (EA), the system adapted the rule base to changing market conditions instead of using a fixed set of rules as most systems do. They developed fuzzy input variables based on price change, portfolio value, simple moving average, two moving average crossover, on balance volume, and alpha, mapping them into seven linguistic values ranging from extremely low to extremely high using triangular membership functions. The output is interpreted as a rating of the strength of a buy recommendation for each rule. Rules were of the form "If price change is high and portfolio value is extremely low then rating is 0.1". The system was tested on MSCI Europe listed stocks over the time period from 1990 to 2005. The EA system was evaluated using a number of performance metrics and compared to a number of benchmark strategies such as the MCSI Europe index, buy and hold, and price momentum. Results showed that the EA system outperformed all the benchmark strategies tested. It is interesting to note that the EA concept presented is similar to the walk-forward optimization and self-adaptive systems optimization techniques discussed by Katz & McCormick (2000, pp. 45-46).

Khcherem & Bouri (2009) used VonAltrock's (1997) fuzzyTECH software to develop a fuzzy model with return, stochastic oscillator, momentum, advance/decline, and new advance/new decline fuzzy variables. The data set used was daily data for 25 firms listed on the Tunisian Stock Exchange from 2001 to 2008. They defined membership functions using low, medium, and high functions for each input variable. They used the first half of the data set as in-sample training data to develop the inference rules using the fuzzyTECH software. The output linguistic value was a buy, hold, or sell recommendation. Testing on the remaining out-of-sample data set showed model accuracy up to 93.26%.

Li & Yang (2008) studied a neuro-fuzzy system applied to the stochastic indicator for four Asian stock markets. The stochastic parameters were mapped to input fuzzy variables and the output was mapped to a fuzzy variable Trend, where a BUY signal was generated when the Trend was above a buy threshold value and a SELL signal was generated when the Trend was below a sell threshold value. A neural network was used to generate and optimize membership functions and the fuzzy rule set from training data over a two year period from 2003 to 2004.

Training was stopped when the model had a rate of return greater than that of a buy and hold strategy in order to avoid over-fitting the model to the training data set. The model was then evaluated on the testing data set over the two year period from 2005 to 2006 against benchmark buy and hold and standard stochastic indicator trading models. Evaluation was based on yearly returns, profit factor, Sharpe ratio, cumulative wealth, maximum drawdown, and average drawdown. The results showed that the neuro-fuzzy system outperformed both benchmark trading models in all of the Asian stock markets tested.

Zhou & Dong (2004) investigated using fuzzy logic to detect technical patterns in stock charts. They used Gaussian kernel-based smoothing and pattern templates based on consecutive local extrema for head-and-shoulders, broadening tops and bottoms, triangle tops and bottoms, and rectangle tops and bottoms. For each pattern, a set of crisp condition variables based on the local extrema defined the pattern. The crisp condition values were converted to fuzzy values using trapezoid membership functions, and the total pattern fuzzy membership value was calculated as the average of the membership values for all the condition variables. The results of their investigation showed that their approach was able to detect subtle differences within a clearly defined pattern template, providing improved precision in detecting technical patterns compared to visual pattern analysis by average investors.

2.6 Conclusions

The review of literature provided information relevant to this project in the following areas:

- Basic principles of technical analysis of financial markets - the concepts of trend and momentum, chart analysis, and mathematical technical indicators.

- Using technical indicators to make trading decisions - how technical indicators are used by stock traders, and how various technical indicators are calculated, indicator model parameters that can be varied to affect the trading model, and trigger conditions for buy and sell signals.
- Methodologies for developing and validating trading systems - timing models for trend following and counter-trend trading strategies, combining technical indicators, optimization, and evaluation.
- Basic elements of fuzzy logic - fuzzy sets, fuzzy inference systems, and fuzzy system applications.
- Using fuzzy logic in trading systems - how fuzzy logic has been applied to trading stocks using technical indicators including optimization techniques, defining linguistic meaning for technical indicator parameters, fuzzy rules that represent the behavior of indicator models, and interpretation of fuzzy output into a buy or sell signal.

Examining the literature in these areas provided information that guided the design and development of a fuzzy logic stock trading system based on technical analysis.

Chapter 3 – Methodology

3.1 Introduction

A two phase methodology was undertaken to develop and evaluate the fuzzy logic trading system based on technical analysis, named Fuzzy Tech, using the guidelines outlined in Table 4.

Table 4 – Development and evaluation methodology

Phase	Guidelines
Development	Historical stock price data Trading models based on technical indicators Trend-following and counter-trend trading models Money management exit models Combine trading models into trading strategies Trading strategies used for simulated or live trading Trading strategy parameter and rule optimization
Evaluation	Genetic optimization is best overall Walk-forward optimization is practical Optimize over large representative recent in-sample data set, multiple of 4-year cycle Test over more recent out-of-sample data to verify consistent performance results Optimize using a minimum number of parameters and rules Optimization should result in a minimum of thirty trades taken Maximize profits and minimize drawdown Compare performance against 200-day moving average

3.2 Trading system development

A block diagram of the system developed with its major components is illustrated in Figure 24.

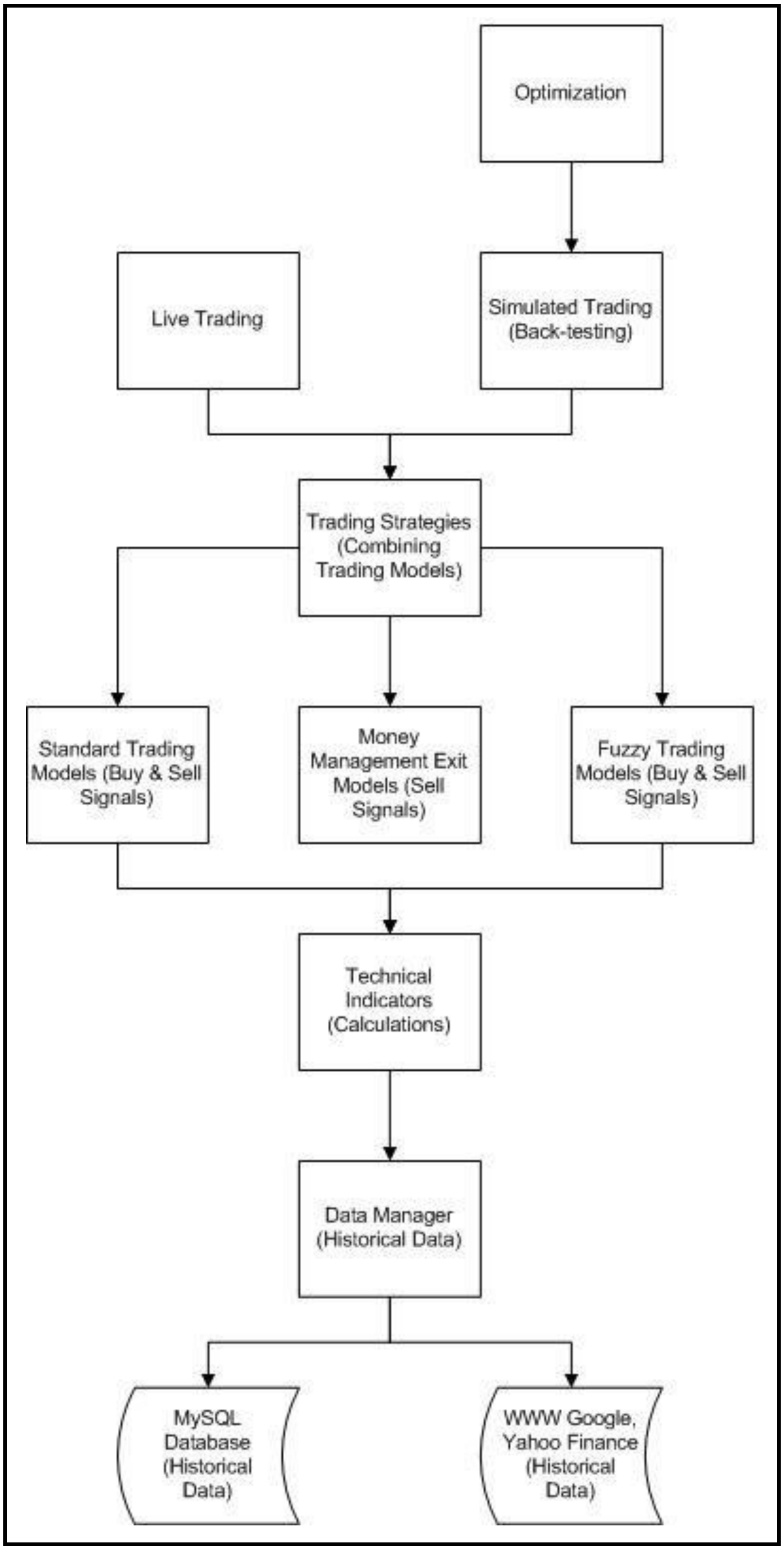


Figure 24 - System block diagram

3.2.1 Data management

The WWW module manages access to historical daily stock price data (Date, Open, High, Low, Close, and Volume) from the Google and Yahoo financial internet web sites. The MySQL Database module manages access to locally stored historical daily stock price data and trading strategy data. The Data Manager manages access to historical daily stock price data and trading strategy data via the WWW and MySQL Database modules. An internal cache of historical stock data improves system performance by minimizing access to those slower access methods. When data is requested, the Data Manager attempts to access the data from internal cache first, then from the local database, and finally from the internet as required.

3.2.2 Technical indicators

Technical indicator modules were built for the following popular technical indicators discussed in section 2.2.2:

- Simple Moving Average
- Exponential Moving Average
- MACD
- Price Channel
- Stochastic
- Relative Strength Index
- Rate of Change
- Bollinger Bands
- On Balance Volume

3.2.3 Trading models

A standard buy-and-hold trading model, ten standard trading models, and ten corresponding fuzzy trading models were developed based on the technical indicators. Four exit models were also developed to provide sell signals based on money management criteria discussed in section 2.3. Table 5 lists the trading models developed, along with their corresponding parameter and rule default values.

Table 5 - Trading model parameter and rule default values

Trading Model Name	Trading Model Parameters	Value	Min	Max	Inc	Trading Model Rules	Enabled
Buy And Hold						BUY on start date	TRUE
						SELL on end date	TRUE
Bollinger Bands	Lookback period (days)	20	5	300	5	BUY if price closes above upper band	TRUE
	Band standard deviations	2	0.5	3.5	0.5	SELL if price closes below lower band	TRUE
						BUY if price closes below lower band	FALSE
						SELL if price closes above upper band	FALSE
Exponential Moving Average	Lookback period (days)	30	5	300	5	BUY if close above moving average	TRUE
						SELL if close below moving average	TRUE
						BUY if today's moving average above yesterday's moving average	TRUE
						SELL if today's moving average below yesterday's moving average	TRUE
MACD	Slow lookback period (days)	26	13	39	1	BUY if histogram is positive	TRUE
	Fast lookback period (days)	12	7	18	1	SELL if histogram is negative	TRUE
	Signal lookback period (days)	9	4	14	1	BUY if MACD line is positive	TRUE
						SELL if MACD line is negative	TRUE
						BUY if Signal line is positive	TRUE
						SELL if Signal line is negative	TRUE
On Balance Volume	OBV moving average lookback period (days)	30	5	300	5	BUY if OBV moves above OBV moving average	TRUE
						SELL if OBV moves below OBV moving average	TRUE
Price Channel	Lookback period (days)	10	5	300	5	BUY if closing price moves above highest high	TRUE
						SELL if closing price moves below lowest low	TRUE

Rate of Change	Lookback period (days)	12	2	300	2	BUY if ROC moves above mid-point (100) level	TRUE
						SELL if ROC moves below mid-point (100) level	TRUE
Relative Strength Index	Lookback period (days)	14	3	50	1	BUY if RSI moves from below oversold level to above oversold level	TRUE
	Oversold level	25	10	40	5	SELL if RSI moves from above overbought level to below overbought level	TRUE
	Overbought level	75	60	90	5	BUY if RSI moves above mid-point (50) level	TRUE
						SELL if RSI moves below mid-point (50) level	TRUE
Simple Moving Average Crossover	Moving average #1 lookback period (days)	10	5	100	5	BUY if moving average #1 above moving average #2	TRUE
	Moving average #2 lookback period (days)	30	10	300	5	SELL if moving average #1 below moving average #2	TRUE
Simple Moving Average	Lookback period (days)	200	5	300	5	BUY if close above moving average	TRUE
						SELL if close below moving average	TRUE
						BUY if today's moving average above yesterday's moving average	FALSE
						SELL if today's moving average below yesterday's moving average	FALSE
Stochastic	%K lookback period (days)	5	1	30	1	BUY if %K moves from below oversold level to above oversold level	TRUE
	%K smoothing lookback period (days, 1=fast stochastic, 3=slow stochastic)	3	1	5	1	SELL if %K moves from above overbought level to below overbought level	TRUE
	%D lookback period (days)	3	1	10	1	BUY if %D moves from below oversold level to above oversold level	TRUE
	Oversold level	25	10	40	5	SELL if %D moves from above overbought level to below overbought level	TRUE
	Overbought level	75	60	90	5	BUY if %K moves above %D	TRUE
						SELL if %K moves below %D	TRUE
Fuzzy Bollinger Bands	Lookback period (days)	20	5	300	5	IF BB_UPPER IS High THEN Signal IS Buy	TRUE
	Band standard deviations	2	0.5	3.5	0.5	IF BB_LOWER IS Low THEN Signal IS Sell	TRUE
	Fuzzy BB Threshold	5	1	25	1	IF BB_LOWER IS Low THEN Signal IS Buy	TRUE
						IF BB_UPPER IS High THEN Signal IS Sell	TRUE
						IF BB_UPPER IS Normal THEN Signal IS Hold	TRUE
						IF BB_LOWER IS Normal THEN Signal IS Hold	TRUE

Fuzzy Exponential Moving Average	Lookback period (days)	30	5	300	5	IF EMA IS High THEN Signal IS Buy	TRUE
	Fuzzy EMA Threshold	5	1	25	1	IF EMA IS Normal THEN Signal IS Hold	TRUE
						IF EMA IS Low THEN Signal IS Sell	TRUE
Fuzzy MACD	Slow lookback period (days)	26	13	39	1	IF HISTOGRAM IS High THEN Signal IS Buy	TRUE
	Fast lookback period (days)	12	7	18	1	IF HISTOGRAM IS Low THEN Signal IS Sell	TRUE
	Signal lookback period (days)	9	4	14	1	IF MACD_LINE IS High THEN Signal IS Buy	TRUE
	Fuzzy MACD Threshold	5	1	25	1	IF MACD_LINE IS Low THEN Signal IS Sell	TRUE
						IF SIGNAL_LINE IS High THEN Signal IS Buy	TRUE
						IF SIGNAL_LINE IS Low THEN Signal IS Sell	TRUE
Fuzzy On Balance Volume	OBV moving average lookback period (days)	30	5	300	5	IF OBV IS High THEN Signal IS Buy	TRUE
	Fuzzy OBV Threshold	5	1	25	1	IF OBV IS Normal THEN Signal IS Hold	TRUE
						IF OBV IS Low THEN Signal IS Sell	TRUE
Fuzzy Price Channel	Lookback period (days)	10	5	300	5	IF PC_UPPER IS High THEN Signal IS Buy	TRUE
	Fuzzy PC Threshold	5	1	25	1	IF PC_UPPER IS Normal THEN Signal IS Hold	TRUE
						IF PC_UPPER IS Low THEN Signal IS Sell	TRUE
						IF PC_LOWER IS Low THEN Signal IS Sell	TRUE
						IF PC_LOWER IS Normal THEN Signal IS Hold	TRUE
						IF PC_LOWER IS High THEN Signal IS Buy	TRUE
Fuzzy Rate Of Change	Lookback period (days)	12	2	300	2	IF ROC IS High THEN Signal IS Buy	TRUE
	Fuzzy ROC Threshold	5	1	25	1	IF ROC IS Normal THEN Signal IS Hold	TRUE
						IF ROC IS Low THEN Signal IS Sell	TRUE
Fuzzy Relative Strength Index	Lookback period (days)	14	3	50	1	IF RSI IS Overbought THEN Signal IS Sell	TRUE
	Oversold level	25	10	40	5	IF RSI IS Neutral THEN Signal IS Hold	TRUE
	Overbought level	75	60	90	5	IF RSI IS Oversold THEN Signal IS Buy	TRUE
Fuzzy Simple Moving Average Crossover	Moving average #1 lookback period (days)	10	5	100	5	IF SMA IS High THEN Signal IS Buy	TRUE
	Moving average #2 lookback period (days)	30	10	300	5	IF SMA IS Normal THEN Signal IS Hold	TRUE
	Fuzzy SMA Threshold	5	1	25	1	IF SMA IS Low THEN Signal IS Sell	TRUE
Fuzzy Simple Moving Average	Lookback period (days)	30	5	300	5	IF SMA IS High THEN Signal IS Buy	TRUE

	Fuzzy SMA Threshold	5	1	25	1	IF SMA IS Normal THEN Signal IS Hold	TRUE
						IF SMA IS Low THEN Signal IS Sell	TRUE
Fuzzy Stochastic	%K lookback period (days)	5	1	30	1	IF K IS Overbought THEN Signal IS Sell	TRUE
	%K smoothing lookback period (days, 1=fast stochastic, 3=slow stochastic)	3	1	5	1	IF K IS Neutral THEN Signal IS Hold	TRUE
	%D lookback period (days)	3	1	10	1	IF K IS Oversold THEN Signal IS Buy	TRUE
	Oversold level	25	10	40	5	IF D IS Overbought THEN Signal IS Sell	TRUE
	Overbought level	75	60	90	5	IF D IS Neutral THEN Signal IS Hold	TRUE
						IF D IS Oversold THEN Signal IS Buy	TRUE
Profit Target Exit	Profit target (percent)	50	5	100	5	SELL if gain greater than profit target	TRUE
Stop Loss Exit	Stop loss (percent)	20	5	30	5	SELL if loss greater than stop loss	TRUE
Time Exit	Time (days)	30	5	30	5	SELL after time period	TRUE
Trailing Stop Exit	Trailing stop (percent)	10	5	50	5	SELL if price closes below trailing stop	TRUE

3.2.3.1 Fuzzy model membership functions

Figure 25 defines the fuzzy membership functions for input linguistic variables for the following fuzzy trading models:

- Fuzzy Bollinger Bands Model
- Fuzzy Exponential Moving Average Model
- Fuzzy MACD Model
- Fuzzy On Balance Volume Model
- Fuzzy Price Channel Model
- Fuzzy Rate Of Change Model
- Fuzzy Simple Moving Average Crossover Model
- Fuzzy Simple Moving Average Model

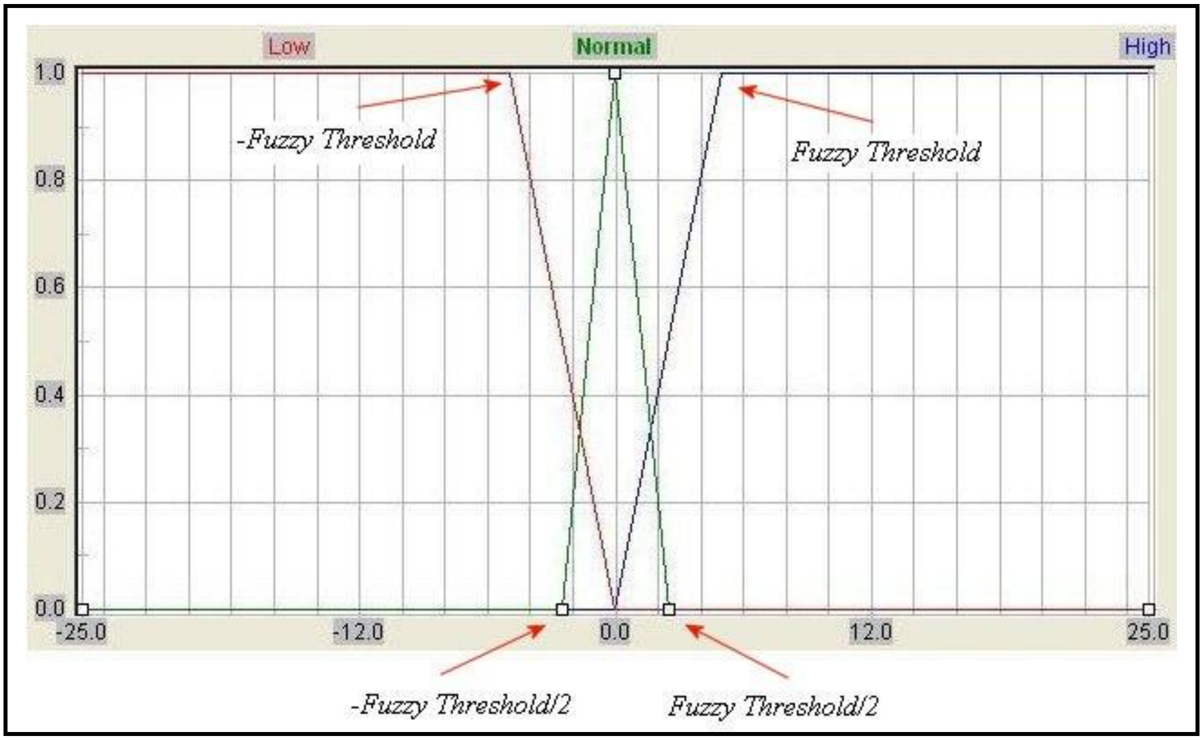


Figure 25 - Membership functions for Fuzzy Threshold input variables

Several of the input variables are normalized values patterned after the technique used by Gamil, El-fouly, & Darwish (2007) and then scaled to -100 to 100. The corresponding parameters and crisp input variables for these trading models were defined as follows:

Fuzzy Bollinger Bands Model

Parameters

Fuzzy Threshold = Fuzzy BB Threshold

Input Variables

BB_UPPER = 100.0 * ((Close – Upper Band Value) / Close)

BB_LOWER = 100.0 * ((Close – Lower Band Value) / Close)

Fuzzy Exponential Moving Average Model

Parameters

Fuzzy Threshold = Fuzzy EMA Threshold

Input Variables

EMA = 100.0 * ((Close – EMA Value) / Close)

Fuzzy MACD Model

Parameters

Fuzzy Threshold = Fuzzy MACD Threshold

Input Variables

HISTOGRAM = Histogram Value

MACD_LINE = MACD Line Value

SIGNAL_LINE = Signal Line Value

Fuzzy On Balance Volume Model

Parameters

Fuzzy Threshold = Fuzzy OBV Threshold

Input Variables

OBV = 100.0 * ((OBV Value – OBV SMA) / OBV Value)

Fuzzy Price Channel Model

Parameters

Fuzzy Threshold = Fuzzy PC Threshold

Input Variables

PC_UPPER = 100.0 * ((Close – Highest High) / Close)

PC_LOWER = 100.0 * ((Close – Lowest Low) / Close)

Fuzzy Rate Of Change Model

Parameters

Fuzzy Threshold = Fuzzy ROC Threshold

Input Variables

ROC = ROC Value - 100.0

Fuzzy Simple Moving Average Crossover Model

Parameters

Fuzzy Threshold = Fuzzy SMA Threshold

Input Variables

SMA = 100.0 * ((SMA1 Value - SMA2 Value) / SMA1 Value)

Fuzzy Simple Moving Average Model

Parameters

Fuzzy Threshold = Fuzzy SMA Threshold

Input Variables

SMA = 100.0 * ((Close – SMA Value) / Close)

Figure 26 defines the fuzzy membership functions for input linguistic variables for the following fuzzy trading models:

- Fuzzy Relative Strength Index Model
- Fuzzy Stochastic Model

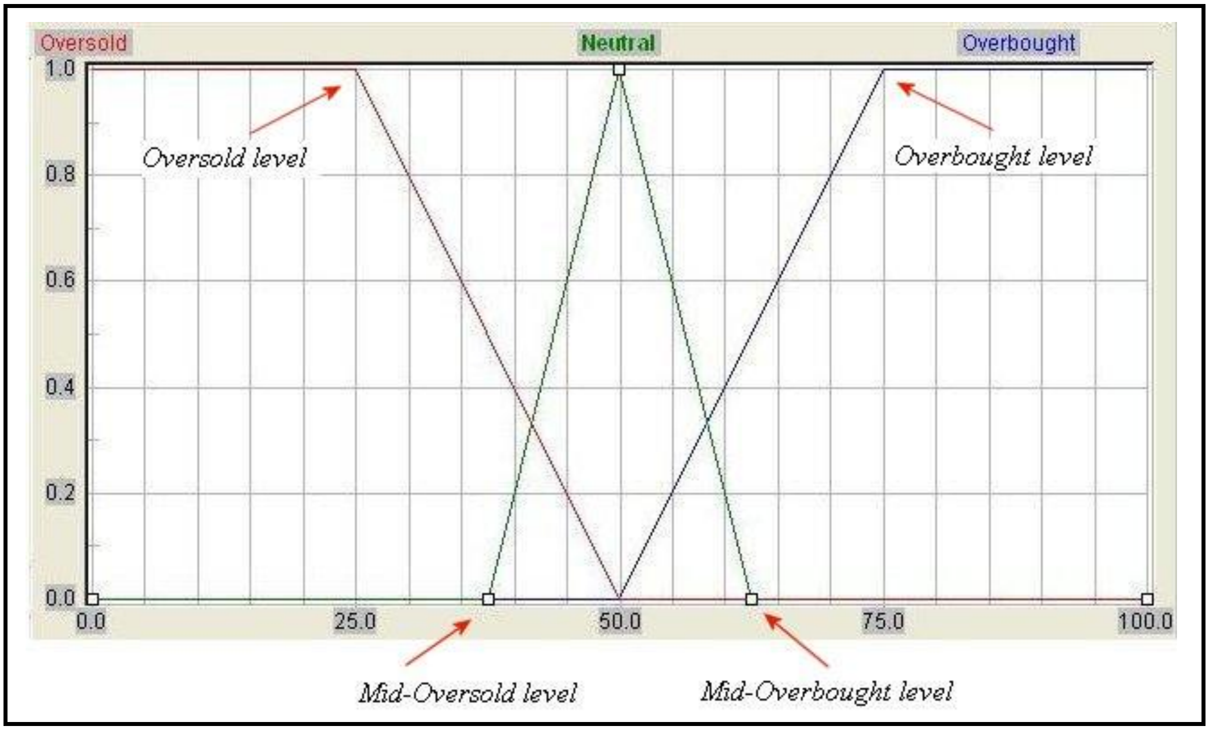


Figure 26 - Membership functions for Overbought/Oversold input variables

The Mid-Oversold and Mid-Overbought level values were defined as follows:

Mid-Oversold level = 50 - ((50 – Oversold level) / 2.0)

Mid-Overbought level = 50 + ((Overbought level - 50) / 2.0).

The corresponding parameters and crisp input variables for these trading models were defined as follows:

Fuzzy Relative Strength Index Model

Parameters

Oversold level

Overbought level

Input Variables

RSI = RSI Value

Fuzzy Stochastic Model

Parameters

Oversold level

Overbought level

Input Variables

K = %K Value

D = %D Value

Figure 27 defines the fuzzy membership functions for the Signal output linguistic variable for all fuzzy trading models. The rule that generates the greatest firing strength provides the resulting sell, hold, or buy trading signal.

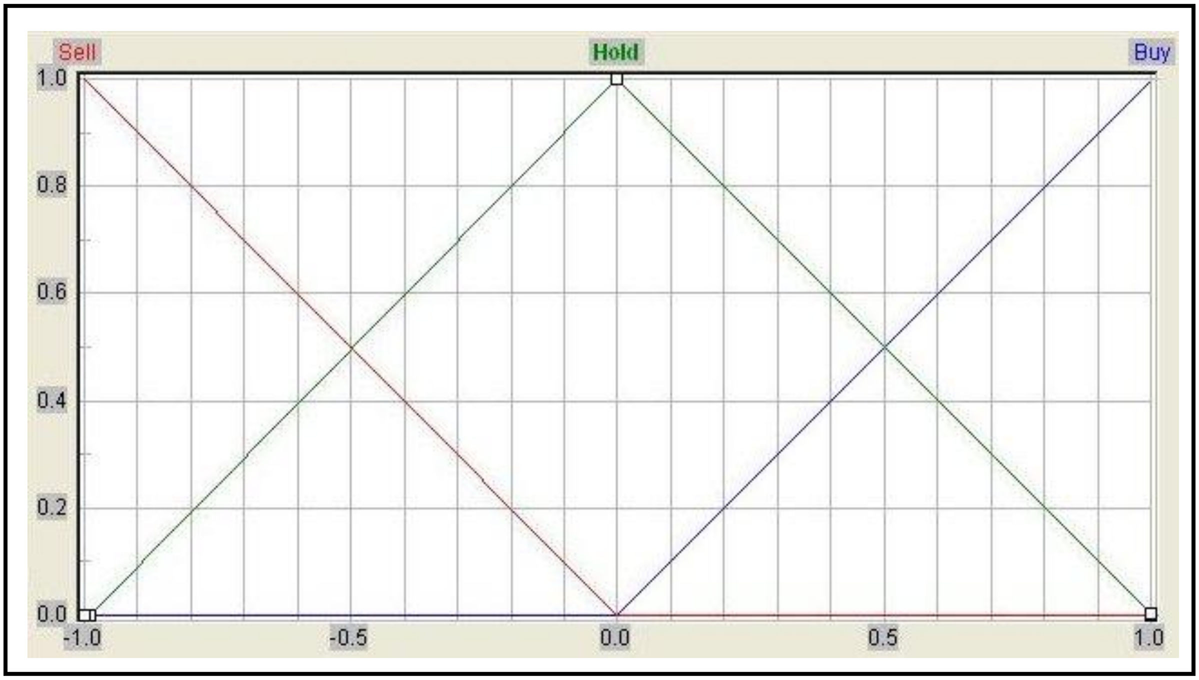


Figure 27 - Membership functions for Signal output variable

As shown in Figure 28, a trading model is defined by its underlying technical indicator, parameters, and rules, which are used to generate trading signals.

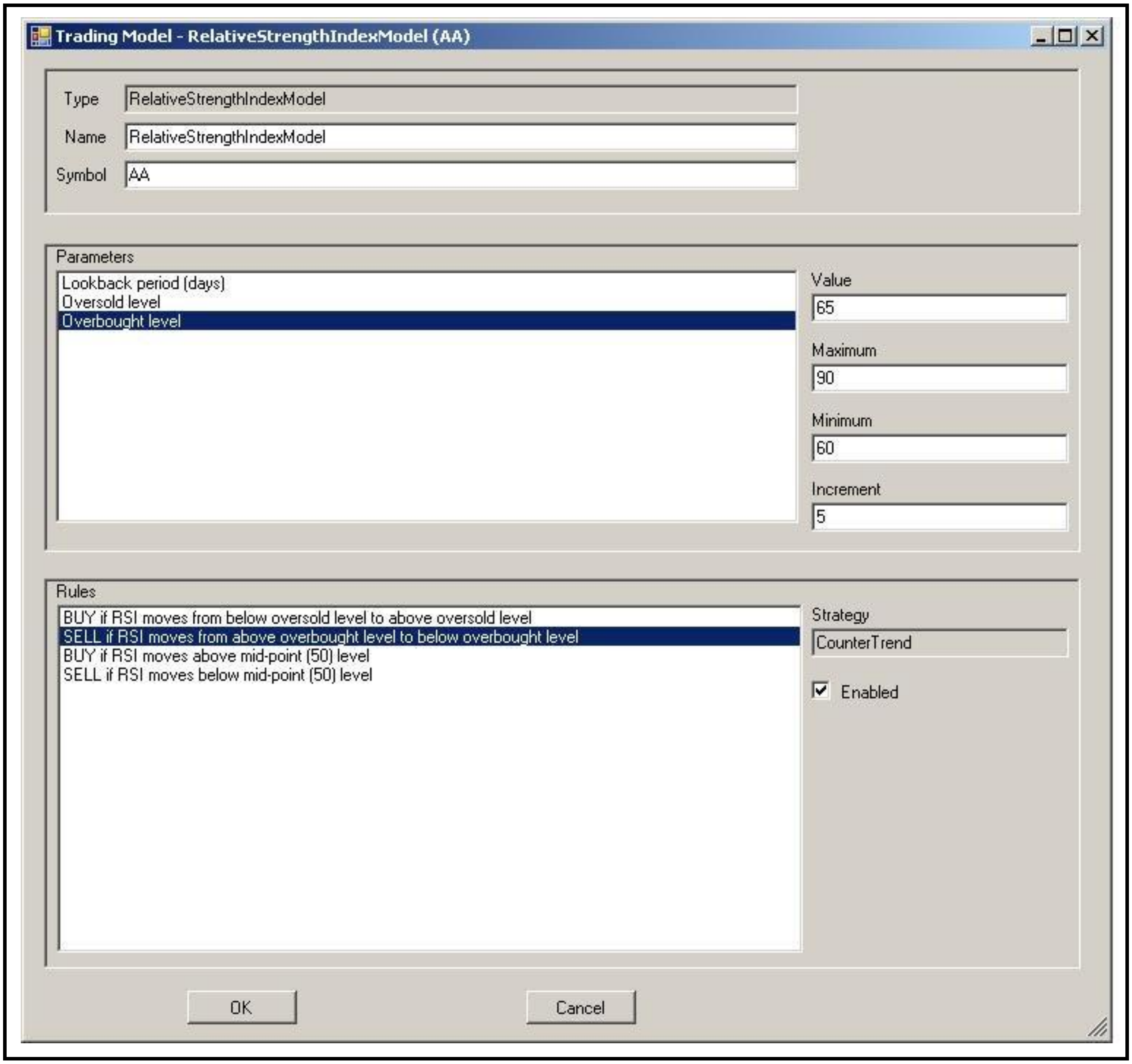


Figure 28 - Trading model

3.2.4 Trading strategies

As shown in Figure 29, a trading strategy is constructed by combining one or more trading models, which generates a composite trading signal based on the trading signals of the component trading models. When editing a trading strategy, right-clicking in the models area allows adding a trading model. To delete a model, select it and press the delete key.

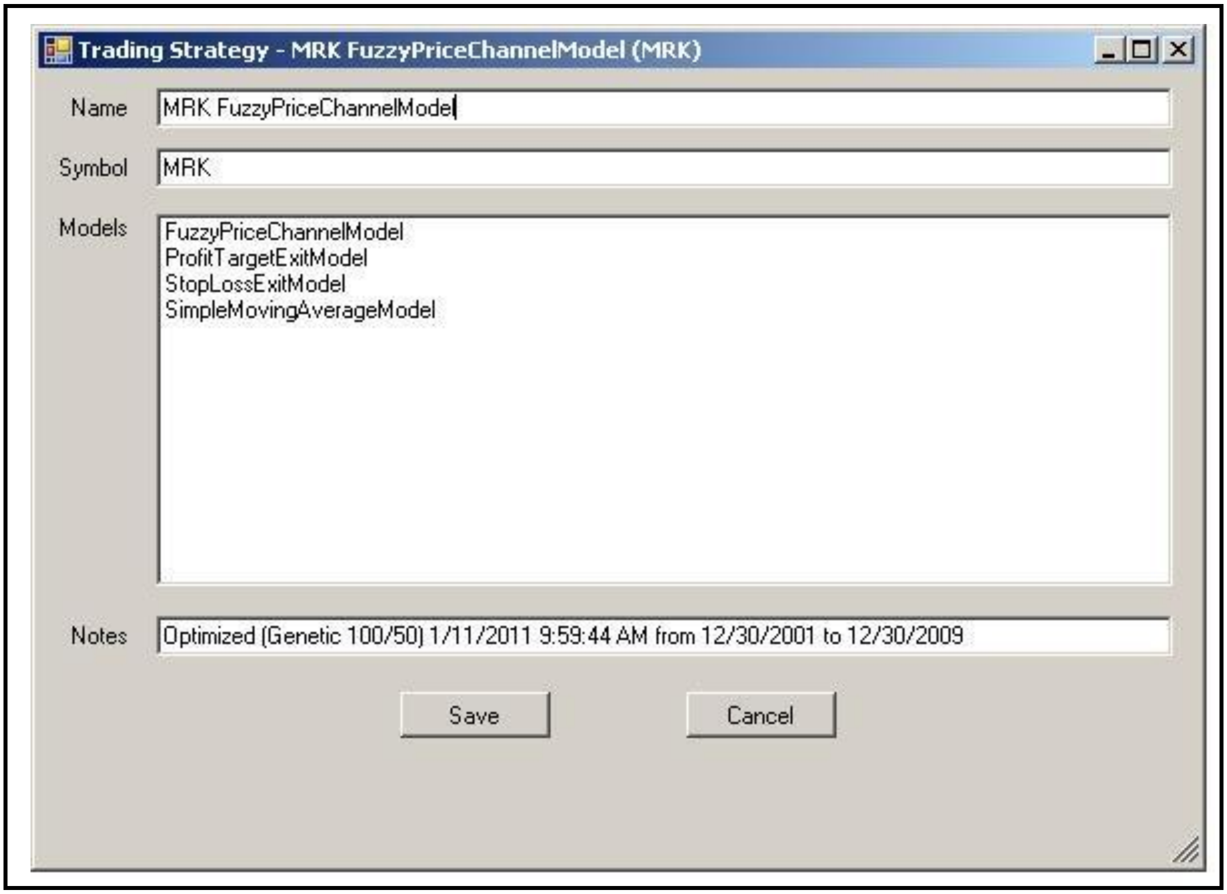


Figure 29 - Trading strategy

3.2.5 Trading simulation

As shown in Figure 30, trading simulation allows back-testing a trading strategy over a period of time to determine its performance results, which can be saved in a Comma Separated Values (CSV) formatted file for later analysis.

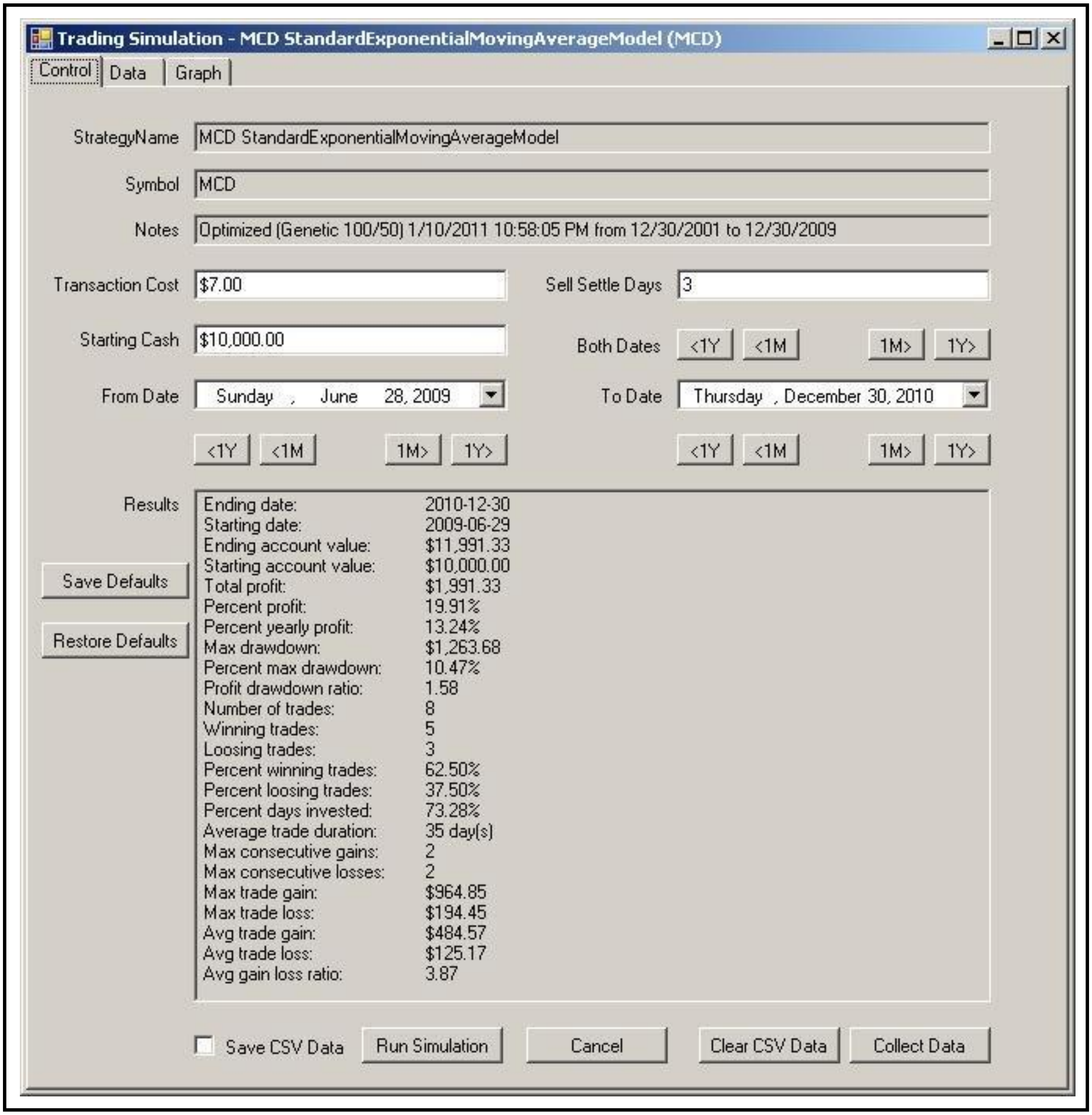


Figure 30 - Trading simulation, control tab

As shown in Figure 31, trading simulation provides detailed trading activity based on trading strategy trading signals.

Date	Close	Signal	Money Management Signal	Action	Cash Value	Shares Owned	Shares Value	Account Value
05/19/2010	$69.40	BUY	HOLD	HOLD	$48.50	168	$11,659.20	$11,707.70
05/20/2010	$67.66	BUY	HOLD	HOLD	$48.50	168	$11,366.88	$11,415.38
05/21/2010	$67.86	BUY	HOLD	HOLD	$48.50	168	$11,400.48	$11,448.98
05/24/2010	$67.66	BUY	HOLD	HOLD	$48.50	168	$11,366.88	$11,415.38
05/25/2010	$67.84	BUY	HOLD	HOLD	$48.50	168	$11,397.12	$11,445.62
05/26/2010	$66.01	SELL	HOLD	SELL	$11,131.18	0	$0.00	$11,131.18
05/27/2010	$67.20	BUY	HOLD	HOLD	$11,131.18	0	$0.00	$11,131.18
05/28/2010	$66.87	SELL	HOLD	HOLD	$11,131.18	0	$0.00	$11,131.18
06/01/2010	$66.36	SELL	HOLD	HOLD	$11,131.18	0	$0.00	$11,131.18
06/02/2010	$67.77	SELL	HOLD	HOLD	$11,131.18	0	$0.00	$11,131.18
06/03/2010	$67.85	BUY	HOLD	BUY	$64.63	163	$11,059.55	$11,124.18
06/04/2010	$66.70	SELL	HOLD	SELL	$10,929.73	0	$0.00	$10,929.73
06/07/2010	$66.75	SELL	HOLD	HOLD	$10,929.73	0	$0.00	$10,929.73
06/08/2010	$68.38	SELL	HOLD	HOLD	$10,929.73	0	$0.00	$10,929.73
06/09/2010	$68.26	SELL	HOLD	HOLD	$10,929.73	0	$0.00	$10,929.73
06/10/2010	$69.37	SELL	HOLD	HOLD	$10,929.73	0	$0.00	$10,929.73
06/11/2010	$69.54	BUY	HOLD	BUY	$4.95	157	$10,917.78	$10,922.73
06/14/2010	$69.30	BUY	HOLD	HOLD	$4.95	157	$10,880.10	$10,885.05
06/15/2010	$70.40	BUY	HOLD	HOLD	$4.95	157	$11,052.80	$11,057.75
06/16/2010	$70.29	SELL	HOLD	SELL	$11,033.48	0	$0.00	$11,033.48
06/17/2010	$70.05	SELL	HOLD	HOLD	$11,033.48	0	$0.00	$11,033.48
06/18/2010	$69.88	SELL	HOLD	HOLD	$11,033.48	0	$0.00	$11,033.48
06/21/2010	$69.92	SELL	HOLD	HOLD	$11,033.48	0	$0.00	$11,033.48
06/22/2010	$68.64	SELL	HOLD	HOLD	$11,033.48	0	$0.00	$11,033.48
06/23/2010	$68.63	SELL	HOLD	HOLD	$11,033.48	0	$0.00	$11,033.48
06/24/2010	$67.73	SELL	HOLD	HOLD	$11,033.48	0	$0.00	$11,033.48

Figure 31 - Trading simulation, data tab

As shown in Figure 32, trading simulation provides a graphical view of the closing price with trading signals (up arrow=buy, down arrow=sell), and a graphical view of the account equity curve.

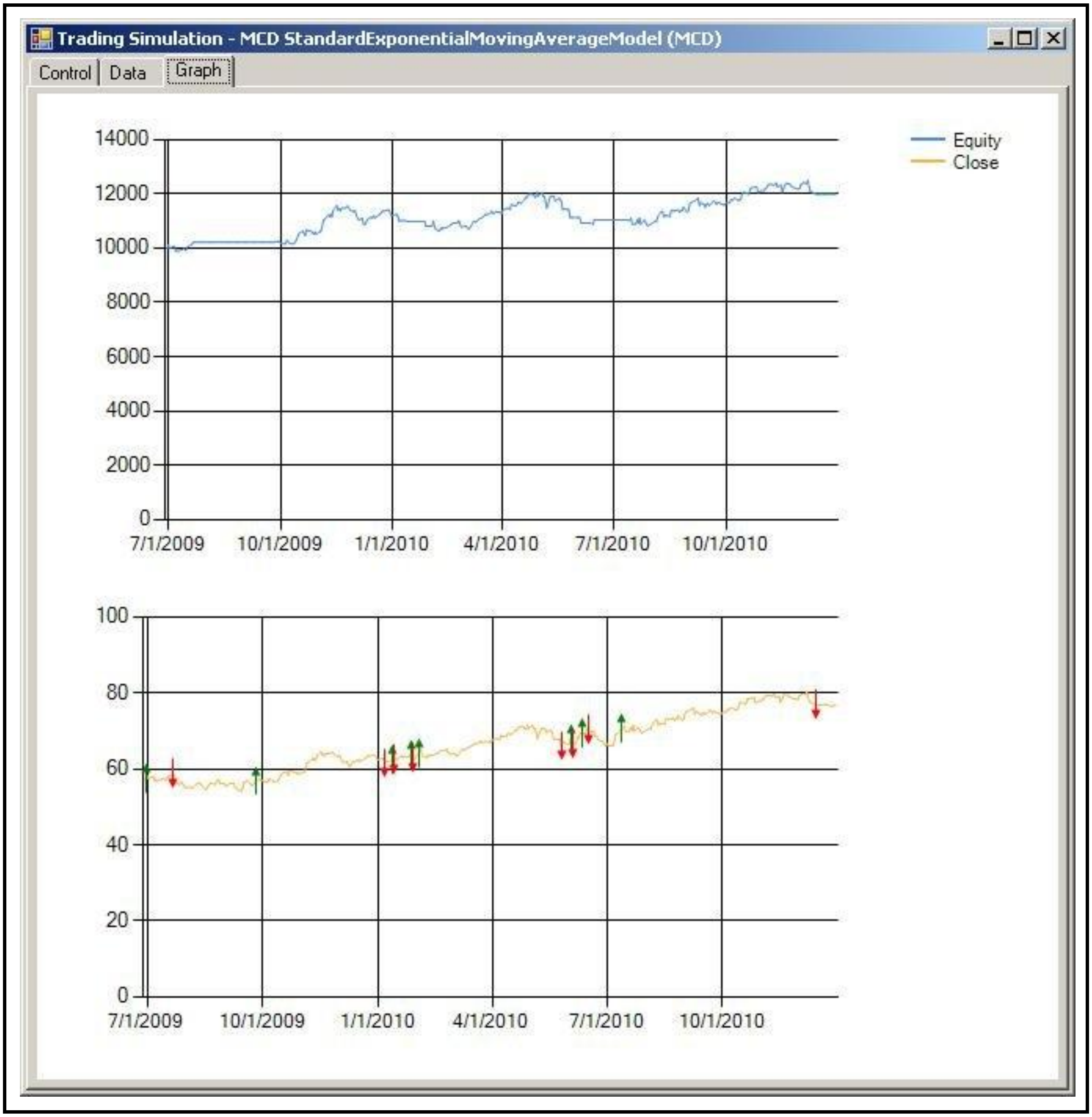


Figure 32 - Trading simulation, graph tab

3.2.6 Strategy optimization

Strategy optimization attempts to find the best combination of trading model parameters and rules by running trade simulations over a period of time using different combinations of trading model parameters and rules. Each trading model parameter value is varied over its minimum to maximum range by its increment value, and trading rules enabled or disabled (see

Figure 28). As shown in Figure 33, there are a number of parameters that control strategy optimization, including transaction cost, sell settle days, starting cash, date range, fitness function, filters, and optimization method.

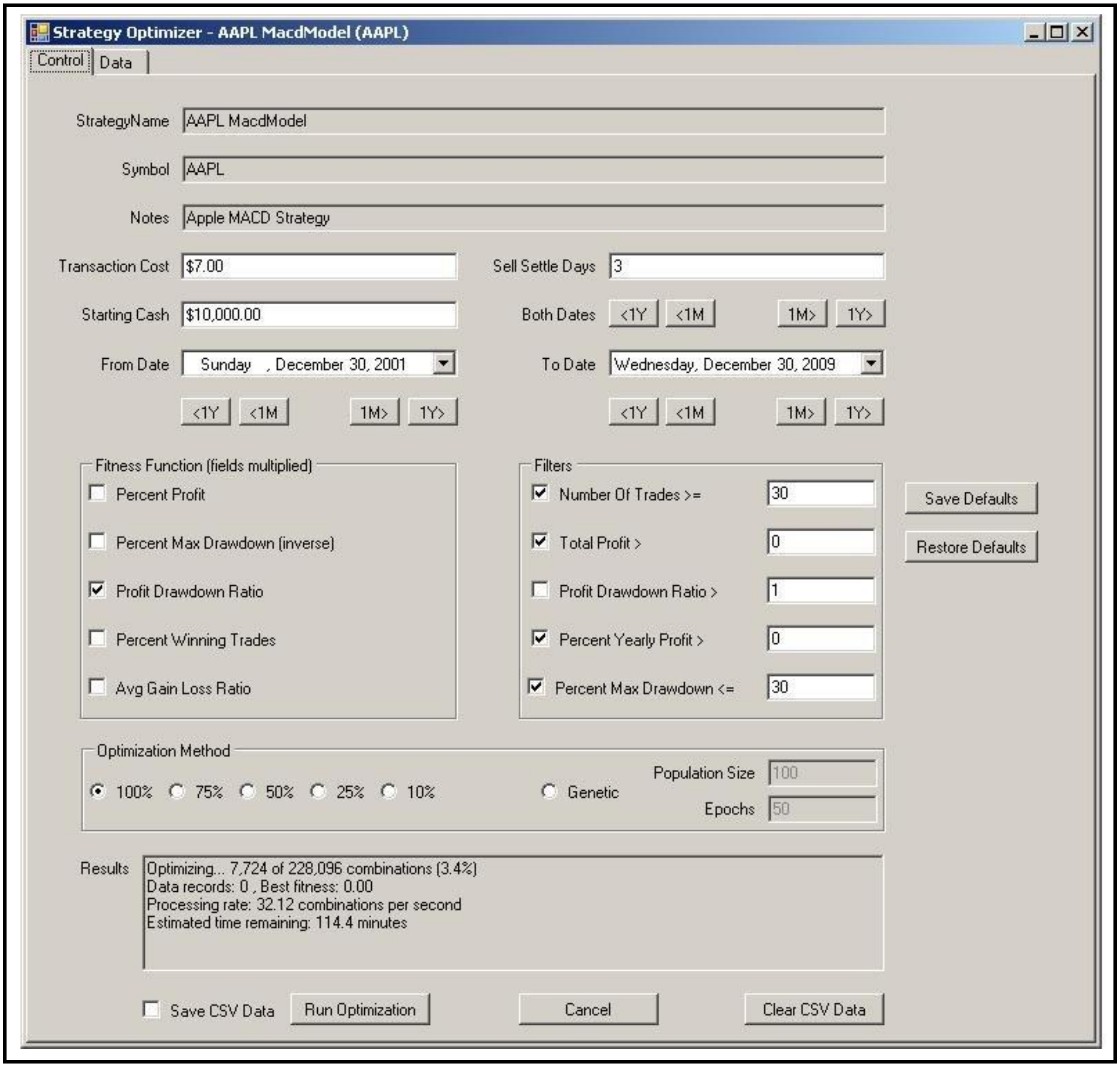
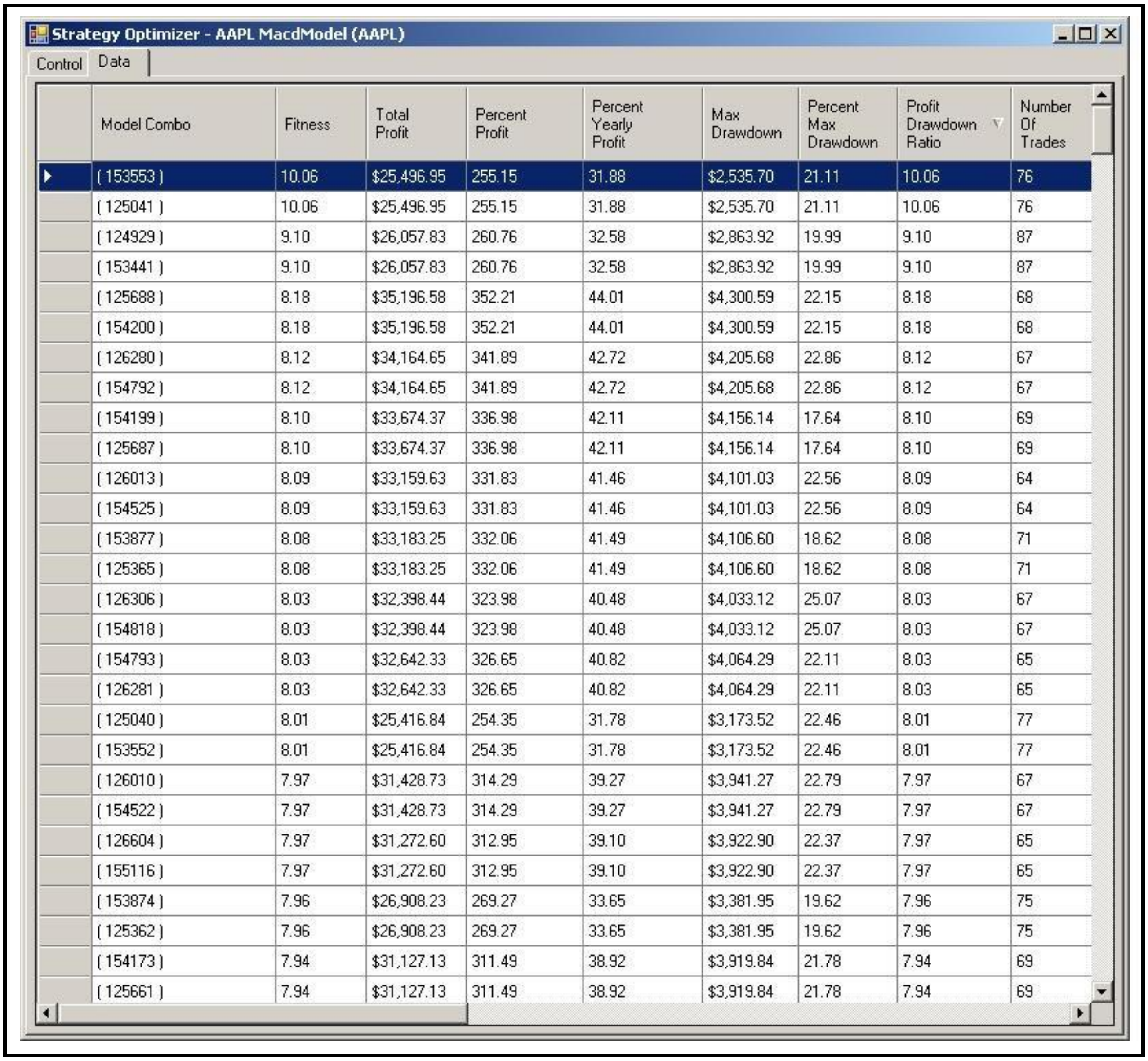


Figure 33 - Strategy optimizer, control tab

The fitness function calculates a fitness value for each resulting strategy, which can be used to compare the performance of different strategies. Filters discard strategies that do not meet the selected filter criteria. The Optimization methods available are exhaustive brute force (100%), random samples (10-75%), or genetic.

When optimization is complete, the data tab is populated with the resulting strategies, as shown in Figure 34. The table can be sorted by clicking a column header, shown here with the resulting optimized strategy list sorted by profit drawdown ratio.



Model Combo	Fitness	Total Profit	Percent Profit	Percent Yearly Profit	Max Drawdown	Percent Max Drawdown	Profit Drawdown Ratio	Number Of Trades
(153553)	10.06	$25,496.95	255.15	31.88	$2,535.70	21.11	10.06	76
(125041)	10.06	$25,496.95	255.15	31.88	$2,535.70	21.11	10.06	76
(124929)	9.10	$26,057.83	260.76	32.58	$2,863.92	19.99	9.10	87
(153441)	9.10	$26,057.83	260.76	32.58	$2,863.92	19.99	9.10	87
(125688)	8.18	$35,196.58	352.21	44.01	$4,300.59	22.15	8.18	68
(154200)	8.18	$35,196.58	352.21	44.01	$4,300.59	22.15	8.18	68
(126280)	8.12	$34,164.65	341.89	42.72	$4,205.68	22.86	8.12	67
(154792)	8.12	$34,164.65	341.89	42.72	$4,205.68	22.86	8.12	67
(154199)	8.10	$33,674.37	336.98	42.11	$4,156.14	17.64	8.10	69
(125687)	8.10	$33,674.37	336.98	42.11	$4,156.14	17.64	8.10	69
(126013)	8.09	$33,159.63	331.83	41.46	$4,101.03	22.56	8.09	64
(154525)	8.09	$33,159.63	331.83	41.46	$4,101.03	22.56	8.09	64
(153877)	8.08	$33,183.25	332.06	41.49	$4,106.60	18.62	8.08	71
(125365)	8.08	$33,183.25	332.06	41.49	$4,106.60	18.62	8.08	71
(126306)	8.03	$32,398.44	323.98	40.48	$4,033.12	25.07	8.03	67
(154818)	8.03	$32,398.44	323.98	40.48	$4,033.12	25.07	8.03	67
(154793)	8.03	$32,642.33	326.65	40.82	$4,064.29	22.11	8.03	65
(126281)	8.03	$32,642.33	326.65	40.82	$4,064.29	22.11	8.03	65
(125040)	8.01	$25,416.84	254.35	31.78	$3,173.52	22.46	8.01	77
(153552)	8.01	$25,416.84	254.35	31.78	$3,173.52	22.46	8.01	77
(126010)	7.97	$31,428.73	314.29	39.27	$3,941.27	22.79	7.97	67
(154522)	7.97	$31,428.73	314.29	39.27	$3,941.27	22.79	7.97	67
(126604)	7.97	$31,272.60	312.95	39.10	$3,922.90	22.37	7.97	65
(155116)	7.97	$31,272.60	312.95	39.10	$3,922.90	22.37	7.97	65
(153874)	7.96	$26,908.23	269.27	33.65	$3,381.95	19.62	7.96	75
(125362)	7.96	$26,908.23	269.27	33.65	$3,381.95	19.62	7.96	75
(154173)	7.94	$31,127.13	311.49	38.92	$3,919.84	21.78	7.94	69
(125661)	7.94	$31,127.13	311.49	38.92	$3,919.84	21.78	7.94	69

Figure 34 - Strategy optimizer, data tab

The time required to optimize a strategy can be significantly affected by the optimization parameters, such as date range, optimization method, and the number of trading model parameter and rule combinations. For example, in Figure 33, 100% optimization of a strategy composed of a MACD trading model over an 8 year period required about 2.8 hours for 228,096 parameter and rule combinations. Using the genetic optimization method with a population size of 100 for 50 epochs reduced optimization time to about 5.4 minutes. There is some trade-off when using the genetic optimization method. In exchange for the speed increase (5.4 minutes vs. 2.8 hours), the genetic optimizer did not find the very best strategy. The top 3 strategies found by the 100% optimization had fitness values 10.06, 9.10, and 8.18. As shown in Figure 35, 10 test runs of the genetic optimizer found strategies with fitness value about 8 most of the time (9 of 10 times) and about 9 only once. The optimizer converged on a solution mid-way through the optimization most of the time.

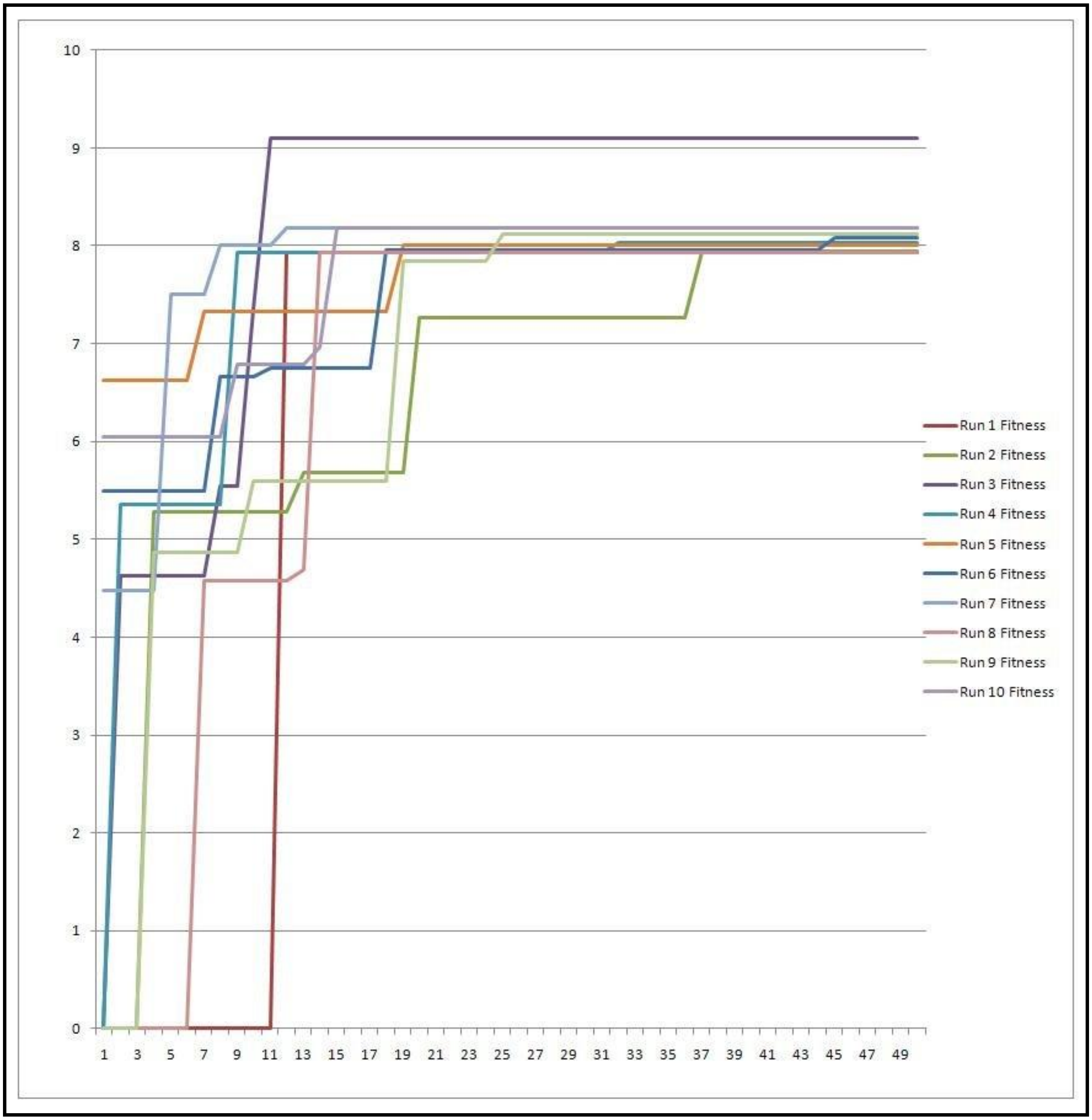


Figure 35 - Genetic optimizer fitness example, Epoch vs. Fitness

Adding a trailing stop exit model to the example strategy increases the parameter and rule combinations to 4,561,920, and would require an estimated 50 hours to optimize. Using the genetic optimization method with a population size of 100 for 50 epochs reduced optimization time to about 8.4 minutes. This example confirms the suggestion in section 2.3.2 that overall the genetic optimizer is a good option when there are a large number of parameter and rule combinations, or when there are a large number of optimizations to perform.

3.3 Trading system evaluation

3.3.1 Data collection methodology

Create Strategy Test Set, as shown in Figure 36, automates the process of creating a set of test data for a group of stocks. For each stock, buy-and-hold and 200-day simple moving average benchmark strategies are created and trading strategies for the 10 standard trading models and the 10 fuzzy trading models are created, as shown in Figure 37. Each of the trading strategies are optimized for the in-sample date range, and trading simulation run on all strategies for the in-sample and out-of-sample date ranges. For each stock, performance data for each trading simulation is collected in a CSV file for further analysis.

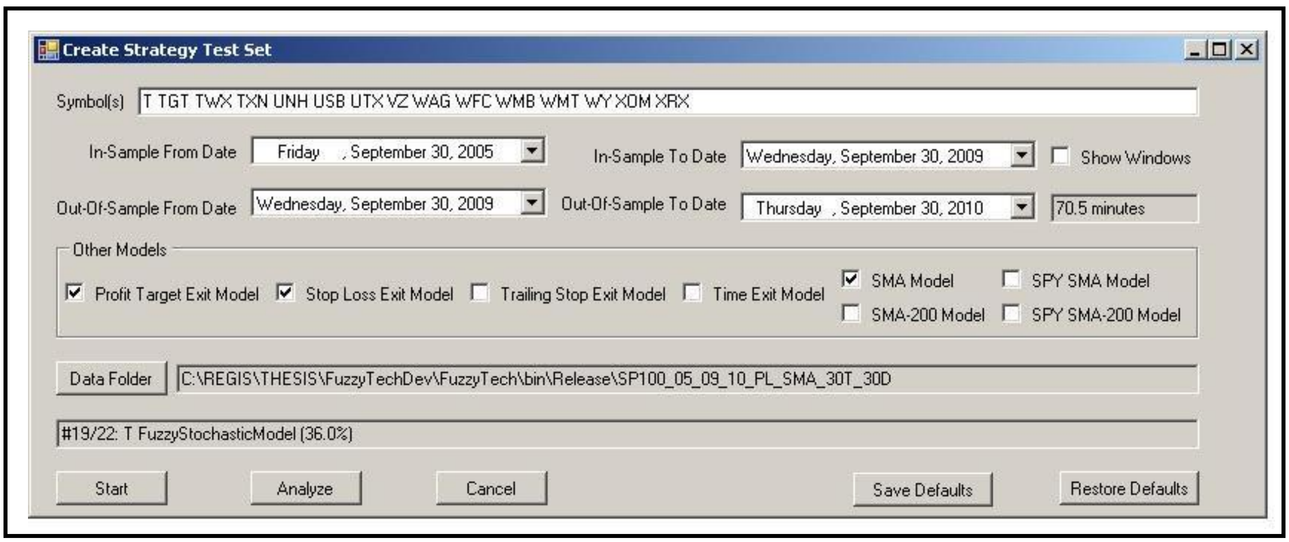
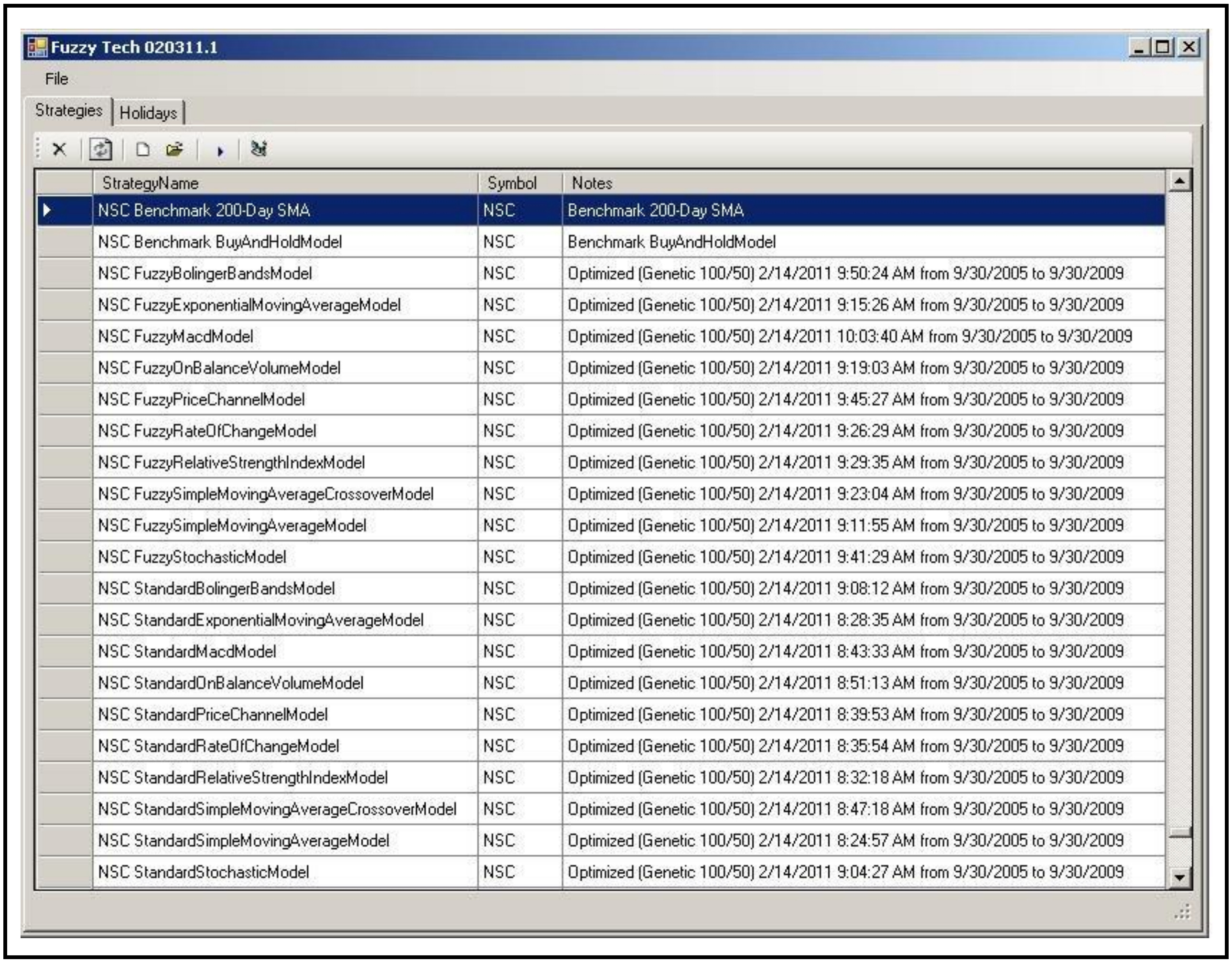


Figure 36 - Create strategy test set



StrategyName	Symbol	Notes
NSC Benchmark 200-Day SMA	NSC	Benchmark 200-Day SMA
NSC Benchmark BuyAndHoldModel	NSC	Benchmark BuyAndHoldModel
NSC FuzzyBolingerBandsModel	NSC	Optimized (Genetic 100/50) 2/14/2011 9:50:24 AM from 9/30/2005 to 9/30/2009
NSC FuzzyExponentialMovingAverageModel	NSC	Optimized (Genetic 100/50) 2/14/2011 9:15:26 AM from 9/30/2005 to 9/30/2009
NSC FuzzyMacdModel	NSC	Optimized (Genetic 100/50) 2/14/2011 10:03:40 AM from 9/30/2005 to 9/30/2009
NSC FuzzyOnBalanceVolumeModel	NSC	Optimized (Genetic 100/50) 2/14/2011 9:19:03 AM from 9/30/2005 to 9/30/2009
NSC FuzzyPriceChannelModel	NSC	Optimized (Genetic 100/50) 2/14/2011 9:45:27 AM from 9/30/2005 to 9/30/2009
NSC FuzzyRateOfChangeModel	NSC	Optimized (Genetic 100/50) 2/14/2011 9:26:29 AM from 9/30/2005 to 9/30/2009
NSC FuzzyRelativeStrengthIndexModel	NSC	Optimized (Genetic 100/50) 2/14/2011 9:29:35 AM from 9/30/2005 to 9/30/2009
NSC FuzzySimpleMovingAverageCrossoverModel	NSC	Optimized (Genetic 100/50) 2/14/2011 9:23:04 AM from 9/30/2005 to 9/30/2009
NSC FuzzySimpleMovingAverageModel	NSC	Optimized (Genetic 100/50) 2/14/2011 9:11:55 AM from 9/30/2005 to 9/30/2009
NSC FuzzyStochasticModel	NSC	Optimized (Genetic 100/50) 2/14/2011 9:41:29 AM from 9/30/2005 to 9/30/2009
NSC StandardBolingerBandsModel	NSC	Optimized (Genetic 100/50) 2/14/2011 9:08:12 AM from 9/30/2005 to 9/30/2009
NSC StandardExponentialMovingAverageModel	NSC	Optimized (Genetic 100/50) 2/14/2011 8:28:35 AM from 9/30/2005 to 9/30/2009
NSC StandardMacdModel	NSC	Optimized (Genetic 100/50) 2/14/2011 8:43:33 AM from 9/30/2005 to 9/30/2009
NSC StandardOnBalanceVolumeModel	NSC	Optimized (Genetic 100/50) 2/14/2011 8:51:13 AM from 9/30/2005 to 9/30/2009
NSC StandardPriceChannelModel	NSC	Optimized (Genetic 100/50) 2/14/2011 8:39:53 AM from 9/30/2005 to 9/30/2009
NSC StandardRateOfChangeModel	NSC	Optimized (Genetic 100/50) 2/14/2011 8:35:54 AM from 9/30/2005 to 9/30/2009
NSC StandardRelativeStrengthIndexModel	NSC	Optimized (Genetic 100/50) 2/14/2011 8:32:18 AM from 9/30/2005 to 9/30/2009
NSC StandardSimpleMovingAverageCrossoverModel	NSC	Optimized (Genetic 100/50) 2/14/2011 8:47:18 AM from 9/30/2005 to 9/30/2009
NSC StandardSimpleMovingAverageModel	NSC	Optimized (Genetic 100/50) 2/14/2011 8:24:57 AM from 9/30/2005 to 9/30/2009
NSC StandardStochasticModel	NSC	Optimized (Genetic 100/50) 2/14/2011 9:04:27 AM from 9/30/2005 to 9/30/2009

Figure 37 - Example strategy test set

Each trading strategy was combined with profit target and stop loss exit models, as well as a simple moving average model. Strategy optimizer and trading simulation used $7 transaction cost, $10,000 starting cash, and 3 sell settle days. Strategy optimizer used profit drawdown ratio as the fitness function; filters were set to ensure optimized strategies were profitable, included a minimum of 30 trades, and a maximum drawdown of 30 percent. Strategies were optimized using the genetic optimization method with population of 100 over 50 epochs.

Strategy test set data were collected for two groups of stocks, DOW30 and S&P100, which are stock market indices that represent 30 and 100 respectively leading publicly owned companies based in the United States.

Some stocks were excluded due to insufficient historical stock price data available, as noted below.

DOW30 stocks included:

AA, AXP, BA, BAC, CAT, CSCO, DD, DIS, GE, HD, HPQ, IBM, INTC, JNJ, JPM, KO, MCD, MMM, MRK, MSFT, PFE, PG, T, TRV, UTX, VZ, WMT, XOM

DOW30 stocks excluded:

CVX, KFT

S&P100 stocks included:

AA, AAPL, ABT, AEP, ALL, AMGN, AVP, AXP, BA, BAC, BAX, BHI, BK, BMY, BRK.B, C, CAT, CL, CMCSA, COF, COP, COST, CPB, CSCO, CVS, DD, DELL, DIS, DOW, DVN, EMC, ETR, EXC, F, FCX, FDX, GD, GE, GILD, HAL, HD, HNZ, HON, HPQ, IBM, INTC, JNJ, JPM, KO, LMT, LOW, MCD, MDT, MMM, MO, MRK, MS, MSFT, NKE, NOV, NSC, NWSA, ORCL, OXY, PEP, PFE, PG, QCOM, RF, SLB, SLE, SO, T, TGT, TWX, TXN, UNH, USB, UTX, VZ, WAG, WFC, WMB, WMT, WY, XOM, XRX

S&P100 stocks excluded:

AMZN, CVX, GOOG, GS, KFT, MA, MET, MON, NYX, PM, RTN, S, UPS

3.3.2 Evaluation methodology

Data were collected over a 12 year period from 9/30/1998 to 9/30/2010 using a walk-forward optimization approach with out-of-sample evaluation over a recent 4-year cycle via a sliding window of 1-year periods. The performance of a portfolio of the 10 best unique stock strategies were evaluated and compared to benchmark strategies.

Data sets were evaluated using an OPTIMIZE-VERIFY-EVALUATE methodology, where strategy test sets were optimized over in-sample data, then verified (optional) over more recent out-of-sample data, and then finally evaluated over another set of even more recent out-of-sample data. In data sets that used no verification period, strategies were selected for the portfolio based on highest profit drawdown ratio. In data sets that did use a verification period, strategies were selected for the portfolio based on highest efficiency factor, which is calculated by multiplying the profit drawdown ratio from the OPTIMIZE and VERIFY data. The efficiency factor represents a measure of how well an optimized stock strategy maintains its performance in subsequent trading simulation, with the expectation that a strategy with high efficiency would continue to perform well in future live or simulated trading.

Data were collected for five data sets, using the naming convention shown in Table 6 based on the number of years for each of the OPTIMIZE-VERIFY-EVALUATE date ranges. The EVALUATE date range was constant for each data set, over a 4-year cycle via a sliding window of 1-year periods, from 9/30/2006 to 9/30/2010.

Table 6 - Data set naming convention

Test Set Name	**OPTIMIZE (years)**	**VERIFY (years)**	**EVALUATE (years)**
401	4	0	1
411	4	1	1
441	4	4	1
801	8	0	1
811	8	1	1

3.3.2.1 Evaluation example

Strategy test set evaluation can be illustrated with an example. Table 7 illustrates stock strategy selection (highlighted and numbered) based on highest efficiency factor for S&P100 test set data with in-sample OPTIMIZE data from 9/30/2000 to 9/30/2004 and out-of-sample

VERIFY data from 9/30/2004 to 9/30/2008. Note that stocks are not selected for the portfolio more than once in order to ensure portfolio diversification.

Table 7 - Example portfolio stock strategy selection based on highest efficiency factor

Name	Starting Date	Ending Date	Percent Yearly Profit	Percent Max Drawdown	Profit Drawdown Ratio	Number Of Trades	Efficiency
01 WY FuzzyStochasticModel	10/2/2000	9/30/2004	20.60	5.32	12.34	30.00	43.07
01 WY FuzzyStochasticModel	9/30/2004	9/30/2008	10.65	10.18	3.49	31.00	43.07
02 LMT FuzzyStochasticModel	10/2/2000	9/30/2004	50.99	10.96	7.57	66.00	37.24
02 LMT FuzzyStochasticModel	9/30/2004	9/30/2008	13.71	8.86	4.92	97.00	37.24
03 NSC StandardBolingerBandsModel	10/2/2000	9/30/2004	53.51	14.62	6.93	44.00	35.69
03 NSC StandardBolingerBandsModel	9/30/2004	9/30/2008	32.26	15.45	5.15	41.00	35.69
04 OXY FuzzyStochasticModel	10/2/2000	9/30/2004	61.30	16.11	10.86	44.00	31.93
04 OXY FuzzyStochasticModel	9/30/2004	9/30/2008	52.41	19.96	2.94	37.00	31.93
05 HAL StandardPriceChannelModel	10/2/2000	9/30/2004	40.87	25.16	5.00	65.00	31.30
05 HAL StandardPriceChannelModel	9/30/2004	9/30/2008	40.25	15.23	6.26	69.00	31.30
06 BAX FuzzyStochasticModel	10/2/2000	9/30/2004	24.57	8.23	6.43	46.00	29.39
06 BAX FuzzyStochasticModel	9/30/2004	9/30/2008	14.45	8.96	4.57	54.00	29.39
07 GILD FuzzyStochasticModel	10/2/2000	9/30/2004	105.35	7.82	9.73	33.00	26.66
07 GILD FuzzyStochasticModel	9/30/2004	9/30/2008	13.40	11.28	2.74	19.00	26.66
08 WFC FuzzyMacdModel	10/2/2000	9/30/2004	26.08	12.59	6.04	35.00	26.52
08 WFC FuzzyMacdModel	9/30/2004	9/30/2008	28.35	14.63	4.39	34.00	26.52
HAL FuzzyBolingerBandsModel	10/2/2000	9/30/2004	53.35	21.29	7.02	68.00	25.34
HAL FuzzyBolingerBandsModel	9/30/2004	9/30/2008	20.33	16.08	3.61	70.00	25.34
GILD FuzzyMacdModel	10/2/2000	9/30/2004	152.61	27.93	10.62	36.00	24.74
GILD FuzzyMacdModel	9/30/2004	9/30/2008	20.84	17.36	2.33	13.00	24.74
09 TGT FuzzyStochasticModel	10/2/2000	9/30/2004	26.10	4.45	14.27	30.00	23.40
09 TGT FuzzyStochasticModel	9/30/2004	9/30/2008	3.98	9.00	1.64	24.00	23.40
HAL FuzzyRelativeStrengthIndexModel	10/2/2000	9/30/2004	45.39	25.13	5.24	63.00	22.17
HAL FuzzyRelativeStrengthIndexModel	9/30/2004	9/30/2008	30.55	14.13	4.23	68.00	22.17
WY StandardMacdModel	10/2/2000	9/30/2004	27.94	8.53	7.81	43.00	21.63
WY StandardMacdModel	9/30/2004	9/30/2008	11.56	15.23	2.77	40.00	21.63
10 CVS FuzzyStochasticModel	10/2/2000	9/30/2004	24.22	7.77	9.84	31.00	21.25
10 CVS FuzzyStochasticModel	9/30/2004	9/30/2008	10.15	14.03	2.16	51.00	21.25

Each selected portfolio stock strategy is then evaluated with out-of-sample EVALUATE data from 9/30/2008 to 9/30/2009. With a starting value of $10,000 for each strategy, Table 8 shows the value at the end of the trading simulation period for the optimized strategies portfolio in the “Strategy Value” column, and totaled on row “Portfolio Value”. The portfolio stocks are also evaluated using benchmark buy-and-hold and 200-day simple moving average trading simulations. In this example, the optimized portfolio strategies outperformed buy-and-hold and 200-day moving average benchmark strategies of the same portfolio stocks.

Table 8 - Example portfolio stock strategy evaluations

Stock Strategy	9/30/2008 - 9/30/2009 Strategy Value	9/30/2008 - 9/30/2009 BuyAndHold Value	9/30/2008 - 9/30/2009 SMA-200 Value
01 WY FuzzyStochasticModel	$7,254.48	$6,061.48	$11,119.79
02 LMT FuzzyStochasticModel	$8,219.69	$7,111.31	$7,727.00
03 NSC StandardBolingerBandsModel	$9,255.45	$6,521.00	$8,897.82
04 OXY FuzzyStochasticModel	$17,386.35	$11,106.95	$12,863.00
05 HAL StandardPriceChannelModel	$11,028.55	$8,362.84	$11,490.50
06 BAX FuzzyStochasticModel	$9,312.45	$8,675.76	$9,837.44
07 GILD FuzzyStochasticModel	$11,250.47	$10,176.53	$8,034.63
08 WFC FuzzyMacdModel	$10,529.40	$7,498.90	$3,757.48
09 TGT FuzzyStochasticModel	$10,637.02	$9,504.89	$10,652.66
10 CVS FuzzyStochasticModel	$10,278.13	$10,601.68	$11,295.44
Portfolio Value	$105,151.99	$85,621.34	$95,675.76

A summary of the 4-year evaluation period includes portfolio stock strategy evaluation totals from each of the 1-year sliding window periods is shown in Table 9, which shows values for each year, as well as average values and percentage of years profitable.

Table 9 - Example walk-forward strategy test set evaluation summary

Portfolio	9/30/2006 - 9/30/2007	9/30/2007 - 9/30/2008	9/30/2008 - 9/30/2009	9/30/2009 - 9/30/2010	Average	Years Profitable
DOW30 Portfolio - Optimized Strategies	$109,535.28	$93,212.89	$102,742.73	$101,838.74	$101,832.41	75%
DOW30 Portfolio - BuyAndHold	$123,059.11	$74,344.58	$88,867.58	$111,975.32	$99,561.65	50%
DOW30 Portfolio - SMA-200	$117,239.72	$81,069.34	$106,001.26	$106,934.47	$102,811.20	75%
DIA - Optimized Strategy	$100,000.00	$97,483.40	$99,501.53	$102,068.44	$99,763.34	25%
DIA - BuyAndHold	$119,131.38	$77,063.36	$89,595.06	$111,119.78	$99,227.40	50%
DIA - SMA-200	$119,138.38	$85,898.06	$112,246.80	$103,211.72	$105,123.74	75%
S&P100 Portfolio - Optimized Strategies	$109,961.37	$90,744.44	$105,151.99	$99,111.97	$101,242.44	50%
S&P100 Portfolio - BuyAndHold	$137,364.53	$82,720.99	$85,621.34	$102,234.82	$101,985.42	50%
S&P100 Portfolio - SMA-200	$124,862.44	$85,484.94	$95,675.76	$97,793.77	$100,954.23	25%
SPY - Optimized Strategy	$111,017.48	$119,496.95	$99,651.36	$106,457.20	$109,155.75	75%
SPY - BuyAndHold	$114,630.50	$75,161.12	$91,021.20	$108,064.84	$97,219.42	50%
SPY - SMA-200	$104,382.77	$91,501.46	$105,539.12	$96,498.91	$99,480.57	50%

In order to provide market comparisons, DIA and SPY optimized and benchmark strategies (see Table 10) are also evaluated by trading simulation using a starting value of $100,000. In this example, only two data sets were profitable, where the SPY 200-day moving average performed slightly better than the S&P100 optimized portfolio strategies. An *Exchange Traded Fund* (ETF) is a tradable security that tracks a group of stocks and can be traded the same way individual stocks can. DIA is an ETF that tracks the DOW30 market index. SPY is an ETF that tracks the S&P500 market index, used because no S&P100 ETF with sufficient historical data was available.

Table 10 - Example DIA & SPY strategy selections based on highest efficiency factor

Name	Starting Date	Ending Date	Percent Yearly Profit	Percent Max Drawdown	Profit Drawdown Ratio	Number Of Trades	Efficiency
01 DIA FuzzyStochasticModel	10/2/2000	9/30/2004	7.56	5.05	4.82	35.00	3.52
01 DIA FuzzyStochasticModel	9/30/2004	9/30/2008	2.85	13.22	0.73	46.00	3.52
02 SPY FuzzyRelativeStrengthIndexModel	10/2/2000	9/30/2004	4.61	3.47	4.53	36.00	2.22
02 SPY FuzzyRelativeStrengthIndexModel	9/30/2004	9/30/2008	0.79	6.15	0.49	72.00	2.22
DIA StandardBolingerBandsModel	10/2/2000	9/30/2004	9.34	20.18	1.68	42.00	2.05
DIA StandardBolingerBandsModel	9/30/2004	9/30/2008	8.01	19.96	1.22	21.00	2.05
DIA StandardRelativeStrengthIndexModel	10/2/2000	9/30/2004	6.73	12.51	1.72	40.00	0.86
DIA StandardRelativeStrengthIndexModel	9/30/2004	9/30/2008	0.75	5.80	0.50	25.00	0.86
SPY FuzzyRateOfChangeModel	10/2/2000	9/30/2004	8.48	15.24	2.17	36.00	0.11
SPY FuzzyRateOfChangeModel	9/30/2004	9/30/2008	0.45	27.03	0.05	22.00	0.11
DIA FuzzyBolingerBandsModel	10/2/2000	9/30/2004	2.10	11.34	0.67	33.00	0.04
DIA FuzzyBolingerBandsModel	9/30/2004	9/30/2008	0.33	16.96	0.06	34.00	0.04

Chapter 4 – Project Analysis and Results

4.1 Data collected

The data collected are a result of approximately 4,360 hours of continuous computing, as shown in Table 11. Equipment used for data collection included a suite of up to five contemporary personal computers.

Table 11 - Data collection hours

Data set type	**Approximate hours per data set**	**Data sets**	**Hours**
S&P100 8-year optimize	400	4	1600
DOW30 8-year optimize	150	4	600
S&P100 4-year optimize	180	9	1620
DOW30 4-year optimize	60	9	540
Total Hours			4,360

4.2 Optimized portfolio strategies

Table 12 summarizes the optimized portfolio strategies selected for all of the data sets collected. It shows that the fuzzy strategies dominated the standard strategies, based on the following observations:

- Fuzzy strategy selection (81.1%) far exceeded that of the standard strategies (18.9%).
- The top three strategies are fuzzy strategies, and represent 76% of all strategies selected.
- The top six strategies, those selected more than two percent of the time, represent 94% of all strategies selected, with four of the six being fuzzy strategies.

Table 12 - Test set portfolio strategies summary

Portfolio Strategy	**Count**	**Percent**
Fuzzy Stochastic	167	43.9%
Fuzzy Relative Strength Index	63	16.6%
Fuzzy MACD	58	15.3%
Standard MACD	30	7.9%

Standard Stochastic	30	7.9%
Fuzzy Price Channel	9	2.4%
Standard Bollinger Bands	6	1.6%
Fuzzy Bollinger Bands	4	1.1%
Fuzzy Exponential Moving Average	3	0.8%
Fuzzy Rate Of Change	2	0.5%
Standard Relative Strength Index	2	0.5%
Fuzzy On Balance Volume	1	0.3%
Fuzzy Simple Moving Average Crossover	1	0.3%
Standard Price Channel	1	0.3%
Standard Rate Of Change	1	0.3%
Standard Simple Moving Average Crossover	1	0.3%
Standard Simple Moving Average	1	0.3%
Fuzzy Strategies	308	81.1%
Standard Strategies	72	18.9%
Total Strategies	380	100.0%

4.3 Test set profit summaries

The following tables present profit summaries, as a percentage, for the five data sets collected, as outlined in section 3.3.2. Each table shows the profit for each 1-year sliding window, the yearly average of the 4-year period, and the percentage of years profitable. The optimized strategy portfolios will be analyzed in comparison to market benchmarks as well as alternative trading portfolios.

Note that the values for the DIA and SPY BuyAndHold and SMA-200 portfolios are the same in each of the tables, since these portfolios are not dependent on the test set portfolios. From the DIA and SPY BuyAndHold portfolios, it can be seen that year 1 was a strong up year for the markets, year 2 was a strong down year, year 3 was a moderate down year, and year 4 was a moderate up year.

4.3.1 Test set 401 profit summaries

Table 13 shows the profit summaries for test set 401, with a 4-year optimization period and no verification period.

Table 13 - Test set 401 profit summaries

Portfolio	**9/30/2006 - 9/30/2007 Profit - yr 1**	**9/30/2007 - 9/30/2008 Profit - yr 2**	**9/30/2008 - 9/30/2009 Profit - yr 3**	**9/30/2009 - 9/30/2010 Profit - yr 4**	**Average Profit**	**Years Profitable**
DOW30 Portfolio - Optimized Strategies	9.0%	-7.9%	1.1%	-1.5%	0.2%	50%
DOW30 Portfolio - BuyAndHold	20.4%	-24.8%	-4.1%	14.1%	1.4%	50%
DOW30 Portfolio - SMA-200	15.9%	-17.0%	10.4%	8.5%	4.5%	75%
DIA - Optimized Strategy	9.5%	-18.8%	-10.6%	0.6%	-4.8%	50%
DIA - BuyAndHold	19.1%	-22.9%	-10.4%	11.1%	-0.8%	50%
DIA - SMA-200	19.1%	-14.1%	12.2%	3.2%	5.1%	75%
S&P100 Portfolio - Optimized Strategies	21.4%	-4.2%	14.4%	3.3%	8.7%	75%
S&P100 Portfolio - BuyAndHold	38.7%	-26.1%	-8.6%	2.4%	1.6%	50%
S&P100 Portfolio - SMA-200	22.3%	-20.4%	-5.9%	-1.1%	-1.3%	25%
SPY - Optimized Strategy	4.5%	-10.1%	1.4%	4.6%	0.1%	75%
SPY - BuyAndHold	14.6%	-24.8%	-9.0%	8.1%	-2.8%	50%
SPY - SMA-200	4.4%	-8.5%	5.5%	-3.5%	-0.5%	50%

The DOW30 optimized portfolio performed poorly, with 0.2% average profit and 50% profitable years, although it did better than DIA optimized strategy and buy-and-hold which lost on average. It did limit losses during down years (2 and 3) but did not perform well in up years (1 and 4). DIA SMA-200 performed best in the group, with 5.1% average profit and 75% profitable years.

The S&P100 optimized portfolio performed well, with 8.7% average profit and 75% profitable years, beating all other portfolios. It minimized losses in down year 2, and profited well in down year 3 and in up years (1 and 4).

4.3.2 Test set 411 profit summaries

Table 14 shows the profit summaries for test set 411, with a 4-year optimization period and 1-year verification period.

Table 14 - Test set 411 profit summaries

Portfolio	9/30/2006 - 9/30/2007 Profit - yr 1	9/30/2007 - 9/30/2008 Profit - yr 2	9/30/2008 - 9/30/2009 Profit - yr 3	9/30/2009 - 9/30/2010 Profit - yr 4	Average Profit	Years Profitable
DOW30 Portfolio - Optimized Strategies	12.0%	-4.0%	-5.7%	-2.2%	0.0%	25%
DOW30 Portfolio - BuyAndHold	25.0%	-20.1%	-7.8%	10.2%	1.8%	50%
DOW30 Portfolio - SMA-200	20.6%	-16.4%	3.0%	3.5%	2.7%	75%
DIA - Optimized Strategy	5.8%	-23.5%	-1.3%	2.3%	-4.2%	50%
DIA - BuyAndHold	19.1%	-22.9%	-10.4%	11.1%	-0.8%	50%
DIA - SMA-200	19.1%	-14.1%	12.2%	3.2%	5.1%	75%
S&P100 Portfolio - Optimized Strategies	6.6%	-5.6%	1.2%	9.1%	2.8%	75%
S&P100 Portfolio - BuyAndHold	16.6%	-18.9%	-4.2%	21.2%	3.7%	50%
S&P100 Portfolio - SMA-200	9.0%	-20.1%	-5.6%	14.0%	-0.7%	50%
SPY - Optimized Strategy	14.4%	-12.7%	0.0%	0.9%	0.6%	50%
SPY - BuyAndHold	14.6%	-24.8%	-9.0%	8.1%	-2.8%	50%
SPY - SMA-200	4.4%	-8.5%	5.5%	-3.5%	-0.5%	50%

The DOW30 optimized portfolio performed poorly, with 0% average profit and 25% profitable years, although it did better than DIA optimized strategy and buy-and-hold which lost on average. It did limit losses during down years (2 and 3), did reasonably well in up year 1, but lost in up year 4. DIA SMA-200 performed best in the group, with 5.1% average profit and 75% profitable years.

The S&P100 optimized portfolio had modest gains, with 2.8% average profit and 75% profitable years, and did better than SPY optimized strategy, buy-and-hold, and SMA-200 portfolios. It limited losses during down year 2, had a slight gain in down year 3, modest gains in up year 1, and good gains in up year 4. S&P100 portfolio buy-and-hold performed best in the group, with 3.7% average profit and 50% profitable years.

4.3.3 Test set 441 profit summaries

Table 15 shows the profit summaries for test set 441, with a 4-year optimization period and 4-year verification period.

Table 15 - Test set 441 profit summaries

Portfolio	9/30/2006 - 9/30/2007 Profit - yr 1	9/30/2007 - 9/30/2008 Profit - yr 2	9/30/2008 - 9/30/2009 Profit - yr 3	9/30/2009 - 9/30/2010 Profit - yr 4	Average Profit	Years Profitable

DOW30 Portfolio - Optimized Strategies	9.5%	-6.8%	2.7%	1.8%	1.8%	75%
DOW30 Portfolio - BuyAndHold	23.1%	-25.7%	-11.1%	12.0%	-0.4%	50%
DOW30 Portfolio - SMA-200	17.2%	-18.9%	6.0%	6.9%	2.8%	75%
DIA - Optimized Strategy	0.0%	-2.5%	-0.5%	2.1%	-0.2%	25%
DIA - BuyAndHold	19.1%	-22.9%	-10.4%	11.1%	-0.8%	50%
DIA - SMA-200	19.1%	-14.1%	12.2%	3.2%	5.1%	75%
S&P100 Portfolio - Optimized Strategies	10.0%	-9.3%	5.2%	-0.9%	1.2%	50%
S&P100 Portfolio - BuyAndHold	37.4%	-17.3%	-14.4%	2.2%	2.0%	50%
S&P100 Portfolio - SMA-200	24.9%	-14.5%	-4.3%	-2.2%	1.0%	25%
SPY - Optimized Strategy	11.0%	19.5%	-0.3%	6.5%	9.2%	75%
SPY - BuyAndHold	14.6%	-24.8%	-9.0%	8.1%	-2.8%	50%
SPY - SMA-200	4.4%	-8.5%	5.5%	-3.5%	-0.5%	50%

The DOW30 optimized portfolio had only slight gains, with 1.8% average profit and 75% profitable years, although it did better than DIA optimized strategy and buy-and-hold which lost on average. It limited losses during down year 2, had a modest gain in down year 3, modest gains in up year 1, and slight gains in up year 4. DIA SMA-200 performed best in the group, with 5.1% average profit and 75% profitable years.

The S&P100 optimized portfolio also had only slight gains, with 1.2% average profit and 50% profitable years, although it did better than SPY buy-and-hold and SMA-200 which lost on average. It limited losses during down year 2, had reasonable gains in down year 3, reasonable gains in up year 1, but a slight loss in up year 4. The SPY optimized strategy performed best in the group, with 9.2% average profit and 75% profitable years.

4.3.4 Test set 801 profit summaries

Table 16 shows the profit summaries for test set 801, with an 8-year optimization period and no verification period.

Table 16 - Test set 801 profit summaries

Portfolio	**9/30/2006 - 9/30/2007 Profit - yr 1**	**9/30/2007 - 9/30/2008 Profit - yr 2**	**9/30/2008 - 9/30/2009 Profit - yr 3**	**9/30/2009 - 9/30/2010 Profit - yr 4**	**Average Profit**	**Years Profitable**
DOW30 Portfolio - Optimized Strategies	8.5%	-3.4%	5.1%	-0.2%	2.5%	50%
DOW30 Portfolio - BuyAndHold	25.0%	-18.9%	-10.6%	12.8%	2.1%	50%
DOW30 Portfolio - SMA-200	19.4%	-17.9%	12.7%	7.2%	5.3%	75%
DIA - Optimized Strategy	0.0%	5.4%	4.6%	9.7%	4.9%	75%
DIA - BuyAndHold	19.1%	-22.9%	-10.4%	11.1%	-0.8%	50%

DIA - SMA-200	19.1%	-14.1%	12.2%	3.2%	5.1%	75%
S&P100 Portfolio - Optimized Strategies	6.6%	-3.2%	6.9%	0.2%	2.6%	75%
S&P100 Portfolio - BuyAndHold	15.1%	-14.5%	-8.2%	-5.1%	-3.2%	25%
S&P100 Portfolio - SMA-200	-0.2%	-14.0%	11.5%	0.1%	-0.6%	50%
SPY - Optimized Strategy	7.7%	4.3%	0.0%	4.4%	4.1%	75%
SPY - BuyAndHold	14.6%	-24.8%	-9.0%	8.1%	-2.8%	50%
SPY - SMA-200	4.4%	-8.5%	5.5%	-3.5%	-0.5%	50%

The DOW30 optimized portfolio had modest gains, with 2.5% average profit and 50% profitable years, although it did better than DIA buy-and-hold which lost on average. It limited losses during down year 2, but not in down year 3, modest gains in up year 1, and a slight loss in up year 4. DOW30 SMA-200 performed best in the group, with 5.3% average profit and 75% profitable years.

The S&P100 optimized portfolio had modest gains, with 2.6% average profit and 75% profitable years, although it did better than SPY buy-and-hold and SMA-200 which lost on average. It limited losses during down year 2, had a nice gain in down year 3, modest gains in up year 1, and a very slight gain in up year 4. The SPY optimized portfolio performed best in the group, with 4.1% average profit and 75% profitable years.

4.3.5 Test set 811 profit summaries

Table 17 shows the profit summaries for test set 801, with an 8-year optimization period and 1-year verification period.

Table 17 - Test set 811 profit summaries

Portfolio	**9/30/2006 - 9/30/2007 Profit - yr 1**	**9/30/2007 - 9/30/2008 Profit - yr 2**	**9/30/2008 - 9/30/2009 Profit - yr 3**	**9/30/2009 - 9/30/2010 Profit - yr 4**	**Average Profit**	**Years Profitable**
DOW30 Portfolio - Optimized Strategies		-6.4%	-0.3%	-0.8%	-2.5%	0%
DOW30 Portfolio - BuyAndHold		-27.8%	-7.6%	3.0%	-10.8%	33%
DOW30 Portfolio - SMA-200		-19.0%	0.4%	1.5%	-5.7%	67%
DIA - Optimized Strategy		0.0%	3.0%	-0.2%	0.9%	33%
DIA - BuyAndHold		-22.9%	-10.4%	11.1%	-7.4%	33%
DIA - SMA-200		-14.1%	12.2%	3.2%	0.5%	67%
S&P100 Portfolio - Optimized Strategies		3.5%	0.0%	2.6%	2.0%	67%
S&P100 Portfolio - BuyAndHold		-14.9%	-12.5%	2.6%	-8.3%	33%
S&P100 Portfolio - SMA-200		-14.4%	-13.5%	-0.6%	-9.5%	0%
SPY - Optimized Strategy		-4.1%	4.1%	-1.1%	-0.3%	33%

SPY - BuyAndHold	-24.8%	-9.0%	8.1%	-8.6%	33%
SPY - SMA-200	-8.5%	5.5%	-3.5%	-2.2%	33%

Note that this data set is incomplete; no data was collected for year 1. This is because for this test set, the EVALUATE period of 9/30/2006 to 9/30/2007 would require the OPTOMIZE period to start 9/30/1997, but data were only collected over a 12 year period from 9/30/1998 to 9/30/2010. Therefore, this test set cannot be fully analyzed. However, it appears that the DOW30 optimized portfolio would likely not have performed well, although the S&P100 optimized portfolio likely would have.

4.4 Successful portfolios

Based on section 2.3.3, a portfolio can be considered successful when its average profit is greater than zero and it is profitable in at least 75% of the years in the four year cycle. Table 18 summarizes the successful portfolios from all the test sets, resulting in the following observations:

- Most of the portfolios in the top half of the list did not use a verification period.
- The SPY optimized strategy appears three times in the list, while DIA optimized strategy appears only once.
- The S&P100 optimized portfolio appears three times in the list, while DOW30 optimized portfolio appears only once near the bottom with only 1.8% average profits.
- It is interesting that DOW30 SMA-200 portfolio appears four times. This portfolio is made up of the stocks selected during the DOW30 portfolio optimization, but uses the SMA-200 strategy instead of the portfolio optimized strategies. In other words, the optimization selects the stocks but not the strategies. The S&P100 SMA-200 portfolio did not appear in the list.

- It is interesting to note that DIA SMA-200 is on the list, but SPY SMA-200 is not.

Table 18 - Successful portfolios

Portfolio	Test Set	Average Profit
SPY - Optimized Strategy	441	9.2%
S&P100 Portfolio - Optimized Strategies	401	8.7%
DOW30 Portfolio - SMA-200	801	5.3%
DIA - SMA-200	ALL	5.1%
DIA - Optimized Strategy	801	4.9%
DOW30 Portfolio - SMA-200	401	4.5%
SPY - Optimized Strategy	801	4.1%
DOW30 Portfolio - SMA-200	441	2.8%
S&P100 Portfolio - Optimized Strategies	411	2.8%
DOW30 Portfolio - SMA-200	411	2.7%
S&P100 Portfolio - Optimized Strategies	801	2.6%
DOW30 Portfolio - Optimized Strategies	441	1.8%
SPY - Optimized Strategy	401	0.1%

Chapter 5 – Conclusions

5.1 Research findings

The results of section 4.2 show that as a group the fuzzy trading strategies in the developed trading system significantly outperformed the standard trading strategies, and thus significantly improved overall performance of the system. This confirms that fuzzy logic can have a positive contribution to a successful trading system.

The results of section 4.4 show that the developed system produced a number of successful trading portfolios, which confirms that once a successful trading system has been developed and verified, an average trader can be successful by simply following the trading system's buy and sell signals. The trader need not be an expert at interpreting the underlying technical indicators, or react to price movements emotionally. The trading decisions are made by the trading system, so the only decision that the average trader need make is whether there is enough confidence in the system to commit real money in live trading.

5.2 Lessons learned

Different stocks have different price pattern cycles and the same strategy does not work the same for all stocks, so each stock must be evaluated to determine what strategy works best for that stock. When the trading system creates strategy test sets, it selects the best stock trading strategies which include not only the trading strategy but the corresponding stock as well. This confirms that selecting the right stock may be just as important as the trading strategy (Doeksen, Abraham, Thomas, & Paprzycki, 2005).

Successful trading strategies developed and verified over one time period are no guarantee that they will continue to perform well in other time periods. In order to maximize profits and achieve consistently good performance, a trading system should tightly control investment risks (Colby & Meyers, 1988, pp. 4-17) in order to avoid significant losses. This research diversified investment with portfolios consisting of ten stocks in order to reduce overall risk of significant losses resulting from a single loosing stock strategy.

5.3 Limitations

The results of section 4.4 show the successful portfolios for the 4-year period tested via 1-year sliding windows. In order to increase confidence in a trading system, it can be tested over other time periods to verify that it maintains consistent performance, before committing real money in live trading.

The process to create a strategy test set is fully automated in the system developed, but the process to evaluate, summarize, and analyze the results is a manual process. A significant reduction in time and effort would result by automating more of the evaluation process.

Construction of strategy test sets as designed allow only limited options. It would be more flexible to allow selection of which trading models to include when combining trading models into a trading strategy.

The results of section 4.1 shows that the time required to create a strategy test set can be significant, mainly due to optimization time. Possible ways to reduce optimization time might include:

- Reduce the number of stocks in the data collection group, and possibly reduce the number of stocks in the optimized portfolio. This could be achieved while maintaining portfolio diversification by using ETFs such as DIA and SPY as well as other market index or sector ETFs, instead of individual company stocks. The results of section 4.4 seem to support this idea as the optimized strategies of the index ETFs DIA and SPY performed quite well.

- Distribute processing over multiple computers. This would enable adding computers to reduce execution time, roughly in inverse proportion.
- Reduce the number of trading strategies in the test set. The results of section 4.2 show a concentration of selected strategies in relatively few strategies. Reducing the number of strategies in the test set from twenty to the top six strategies would significantly reduce processing time.

5.4 Future research

As noted in section 4.4, a significant number of successful portfolios did not use a verification period. This seems to contradict conventional wisdom (Colby & Meyers, 1988, pp. 18-19; Katz & McCormick, 2000, pp. 43-45; Weissman, 2005, pp. 148-150) that verification is essential. It also suggests the need to further investigate alternate ways to calculate efficiency factor used in this research, to improve correlation between efficiency factor and maintained performance.

The top strategies as shown in section 4.2 tend be shorter-term trading strategies resulting in relative active trading. In order to allow more flexibility in trading styles, future research could investigate including more optimization filters, such as average trade duration, to allow longer-term as well as shorter-term trading preferences.

Future research might develop additional trading models based on other technical indicators, as well as other trading models that may not correspond to an underlying technical indicator, such as up *x*-days consecutively and *x*-week highs/lows.

This research did not investigate the use of trend filters. Additional research might develop a trend model that signals whether the market is trending or not. This trend filter could signal a trading strategy to use trend-following trading models when price is trending and counter-trend trading models when price is not trending (Katz & McCormick, 2000, pp. 85,102-103,131; Murphy, 1999, pp. 384-387,390; Ruggiero, 1997, pp. 48, 59, 78-80,215,263; Stridsman, 2001, pp. 70,234,241-242,250-253; Weissman, 2005, pp. 27-29, 56-58). The trend filter could also be used to signal a trading strategy to only trade in the direction of the trend (Stridsman, 2001, pp. 70, 87,228).

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This book covers a comprehensive list of technical indicators, providing detailed explanations of how each works including calculations and interpretations. The author's detailed example calculations are particularly useful for anyone developing software implementations.

Ahmad, S., Gayar, N., & Elazim, H. (2006). A fuzzy engine model for efficient stock market prediction. *Proceedings of the 5th WSEAS Int. Conf. on COMPUTATIONAL INTELLIGENCE, MAN-MACHINE SYSTEMS AND CYBERNETICS, Venice, Italy, November 20-22, 2006.* Retrieved June 2, 2010, from http://www.wseas.us/e-library/conferences/2006venice/papers/539-672.pdf

This paper presents a fuzzy engine model that combines popular technical indicators with fuzzy logic to predict stock price movement. The authors found that the fuzzy engine model performed well compared to traditional indicators by providing more reliable buy and sell signals.

Callan, R. (2003). *Artificial intelligence.* New York: Palgrave Macmillan.

This book introduces a range of artificial intelligence topics. The author introduces fuzzy logic modeling as one approach to reasoning under uncertainty using illustrative examples.

Castellano, G., Fanelli, A., & Mencar, C. (2003). Design of transparent Mamdani fuzzy inference systems. *In Design and Application of Hybrid intelligent Systems, IOS Press, Amsterdam, The Netherlands,* 468-476. Retrieved January 16, 2010, from http://www.di.uniba.it/~castellano/papers/HIS2003.pdf.

This paper presents a technique to automatically design fuzzy system rules and input functions based on available data. The authors illustrate the technique and the trade-off between transparency and accuracy when training the system to an available data set by selecting the maximum number of desired rules.

Cheung, W. & Kaymak, U. (2007). A fuzzy logic based trading system. *3rd European Symposium on Nature-inspired Smart Information Systems.* Retrieved January 16, 2010, from http://www.nisis.risk-technologies.com/events/symp2007/papers/BB25_p_kaymak.pdf.

This paper presents a successful fuzzy logic based trading system that uses popular technical indicators, and optimized using a genetic algorithm and historical data. The authors justify using genetic optimization over neural networks because of the increased flexibility in fitness function and efficient search over large solution space without the potential drawback that neural networks have to converge on local optima.

Colby, R. & Meyers, T. (1988). *The encyclopedia of technical market indicators.* New York: Irwin Professional Publishing.

This book provides a thorough background of technical analysis concepts and technical indicators. The authors include a comprehensive list of technical indicators, explaining formulas to calculate and rules to interpret buy and sell trigger conditions. They also discuss how technical indicators can be used to development and validate trading systems.

Cox, E. (1995). *Fuzzy logic for business and industry*. Rockland, MA: Charles River Media, Inc.

This book focuses on the application of fuzzy logic using actual models and case studies from business and industry. The author provides practical examples using modeling concepts and software used in real world applications.

Cox, E. (1999). *The fuzzy systems handbook: A practitioner's guide to building, using, and maintaining fuzzy systems (2nd ed.).* San Diego, CA: Academic Press.

This book provides a comprehensive introduction to fuzzy logic and fuzzy systems design. The author includes a number of real world examples of fuzzy system applications, as well as some software implementations.

Doeksen, B., Abraham, A., Thomas, J., & Paprzycki, M. (2005). Real stock trading using soft computing models, *IEEE International Conference on Information Technology: Coding and Computing (ITCC'05), USA, IEEE Computer Society,* pp. 162-167. Retrieved January 16, 2010, from http://www.softcomputing.net/itcc05_03.pdf.

This paper compares performance of trading systems using neural networks, fuzzy logic, and genetic algorithms. The authors found that picking the correct stock is as important as building the best system. They also found that transaction costs can be significant in trading systems.

Dourra, H. & Siy, P. (2002). Investment using technical analysis and fuzzy logic. *Fuzzy Sets and Systems, 2002. 127:* pp. 221-240. Retrieved June 2, 2010, from http://sedok.narod.ru/s_files/poland/Dourra_Siy.pdf.

This paper presents a fuzzy logic trading system based on several technical indicators. The authors found that the system tested on four company stocks substantially outperformed the S&P 500.

Edwards, R. & Magee, J. (1992). *Technical analysis of stock trends (6th ed.)*. Boston: John Magee Inc.

This book provides a comprehensive foundation of technical analysis that covers the time-tested as well as contemporary trading and investing techniques. The authors cover the analysis of stock trends, chart analysis and technical patterns, and much more.

Gamil, A., El-fouly, R., & Darwish, N. (2007). Stock technical analysis using multi agent and fuzzy logic. *Proceedings of the World Congress on Engineering 2007 Vol I, WCE 2007, July 2 - 4, 2007, London, U.K.* Retrieved January 16, 2010, from http://www.iaeng.org/publication/WCE2007/WCE2007_pp142-147.pdf.

This paper presents a fuzzy logic trading system based on technical analysis. Input fuzzy variables are based on several simple moving averages with varying look-back periods. The authors found that by tuning the system with genetic algorithms satisfactory results were achieved.

Ghandar, A., Michalewicz, Z., Schmidt, M., To, T., and Zurbrugg, R. (2009). Computational intelligence for evolving trading rules. *Evolutionary Computation, IEEE Transactions on*, 13(1):71-86. Retrieved June 2, 2010, from http://www.finheuristics.com/doc/technicalpaper.pdf.

This paper presents a fuzzy logic trading system that uses an evolutionary algorithm to adapt trading rules dynamically based on market conditions. The authors found that the evolutionary approach was a significant improvement over fixed rule-based strategies.

Katz, J. & McCormick, D. (2000). *The encyclopedia of trading strategies.* New York: McGraw-Hill.

This book explores methodologies for trading system development and evaluation. The authors take a systematic approach for trading strategy development, back-testing, and optimization techniques.

Khcherem & Bouri. (2009). Fuzzy logic and investment strategy. *Global Economy & Finance Journal Vol. 2 No. 2 September 2009*, pp. 22-37. Retrieved June 2, 2010, from http://wbiaus.org/2.Fatma-Lestet.pdf.

This paper presents a fuzzy logic trading system using technical indicators that was tested on the Tunisian stock exchange. The authors found that for 25 stocks tested, the system had 93.26% accuracy.

Li, J. & Yang J. (2008). A trading decision support system based on neuro-fuzzy technique: Evidence from Asian stock market. *Journal of International Management Studies, February 2008*, pp. 235-242. Retrieved June 2, 2010, from http://www.jimsjournal.org/28%20Jia-Hao%20Li.pdf.

This paper presents a neuro-fuzzy trading system based on the stochastic technical indicator. The authors tuned the system using a neural network and tested it on Asian stock markets and found that it outperformed benchmark buy-and-hold and traditional stochastic strategies.

Miner, R. (2009). *High probability trading strategies: Entry to exit tactics for the forex, futures, and stock markets.* Hoboken, N.J.: John Wiley & Sons, Inc.

This book outlines a practical trading plan that the author has developed in over twenty year experience. The author explains how to use simple pattern and timing strategies to identify trend reversal, including a multiple time frame momentum strategy.

Murphy, J. (1999). *Technical analysis of the financial markets: A comprehensive guide to trading methods and applications.* New York: New York Institute of Finance.

This book provides an excellent reference on the concepts of technical analysis and their application. The author describes many technical indicators, including examples using charts as well as clear explanations.

Popoola, A., Ahmad, S. & Ahmad, K. (2004). A fuzzy-wavelet method for analyzing non-stationary time series. *In Proc. of The 5th Int. Conf. on Recent Advances in Soft Computing (December 16-18, 2004, Nottingham, UK).* Retrieved March 3, 2010, from http://www.computing.surrey.ac.uk/grid/fingrid/papers_files/Reports/12.pdf.

This paper presents a time series analysis approach using wavelet analysis and fuzzy modeling. The authors demonstrate a fuzzy-wavelet prediction method to create fuzzy rules from a decomposed non-stationary time series and found that the fuzzy-wavelet approach performs better than pure fuzzy modeling.

Rao, V. & Rao, H. (1993). *C++ neural networks and fuzzy logic.* New York: Management Information Source, Inc.

This book provides C++ programming examples for neural networks and fuzzy logic. The authors cover some background theory of the technologies used in the examples.

Renz, C. (2004). *The investor's guide to technical analysis.* New York: McGraw-Hill.

This book provides an introduction to the basic concepts of technical analysis and chart interpretation. The author uses straightforward examples that clearly illustrate practical trading strategies using chart pattern analysis.

Ruggiero, M. (1997). *Cybernetic trading strategies: Developing a profitable trading system with state-of-the-art technologies.* New York: John Wiley & Sons, Inc.

This book explains how advanced technologies such as neural networks, fuzzy logic, genetic algorithms, and others can be used to develop tradable market timing systems. The author illustrates how these technologies can be incorporated into traditional technical analysis strategies to greatly improve standard trading system performance.

Russell, S. & Norvig, P. (2003). *Artificial Intelligence: A modern approach* (2nd ed.). Upper Saddle River, N.J.: Pearson Educational, Inc.

This book introduces basic ideas in artificial intelligence. The author includes a brief overview of fuzzy sets using a simple example.

Schwager, J. (1999). *Getting started in technical analysis.* New York: John Wiley & Sons, Inc.

This book explains the basic concepts of technical analysis such as trends, trading ranges, and chart patterns. The author's clear and simple explanations provide a framework for using technical analysis as the basis for trend-following and counter-trend mechanical trading systems.

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This internet web site is home of the TekView Explorer investment software. The web site discusses how fuzzy logic is used in the software to create and back-test trading strategies.

Stridsman, T. (2001). *Trading systems that work: Building and evaluating effective trading systems.* New York: McGraw-Hill.

This book provides guidelines for designing and evaluating rule-based mechanical trading systems. The author discusses risk and money management techniques to maximize profit and minimize risk.

StockCharts.com. (2010). Multicollinearity. Retrieved May 27, 2010, from http://stockcharts.com/school/doku.php?id=chart_school:trading_strategies:multicollinearity.

This internet web page presents the concept of multicollinearity, using the same type of information more than once. The author discusses the problem of a trading strategy composed of multiple technical indicators that contribute redundant information.

VonAltrock, C. (1997). *Fuzzy logic & neurofuzzy applications in business & finance.* Upper Saddle River, N.J.: Prentice-Hall, Inc.

This book illustrates the use of fuzzy logic in the design of business and financial applications, and includes a demonstration version of the author's *fuzzyTECH* software. The author presents numerous case studies and explains the use of the software in the implementation of fuzzy systems.

Weissman, R. (2005). *Mechanical trading systems: Pairing trader psychology with technical analysis.* Hoboken, N.J.: John Wiley & Sons, Inc.

This book examines the development of mechanical trading systems using technical analysis. The author discusses many related issues such as back-testing, risk management, and optimization.

Zhizhin, M., Poyda, A., Mishin, D., Medvedev, D., Kihn, E., & Lutsarev, V. (2006). Scenario search on the grid of environmental data sources. MSR Technical Report, July 2006. Retrieved February 7, 2010, from http://research.microsoft.com/pubs/68030/tr-2006-72.pdf.

This paper presents a system for distributed querying and mining of large environmental data archives. The authors describe how the system uses fuzzy logic to allow users to query the data in meaningful human linguistic terms.

Zhou, X. & Dong, M. (2004, July/August). Can fuzzy logic make technical analysis 20/20? *Financial Analysts Journal, Vol. 60, No. 4,* pp. 54-73. Retrieved January 16, 2010, from http://www.cs.wayne.edu/~mdong/fuzzytech.pdf.

This paper presents a fuzzy logic-based method to detect technical patterns in stock charts. The authors found that the approach can detect subtle differences by using clearly defined pattern templates.