# A Fuzzy Logic Based Trading System

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ABSTRACT: Technical analysis is sometimes used in financial markets to assist traders make buying and selling decisions. The success of technical analysis depends on how one interprets the available signals. Integration of human expertise into available models is considered to be essential for this purpose. Fuzzy systems could be used for developing decision models in which the experience of a trader can be incorporated in a natural way. In this paper, we examine a trading model that combines fuzzy logic and technical analysis to find patterns and trends in financial indices. The rule base of the fuzzy system is kept relatively straightforward for enhancing the interpretability of the model. The fuzzy model is optimised by using a genetic algorithm and historical data. The empirical results show that the proposed model is capable of generating higher risk-discounted returns in the out-of-sample periods compared to a buy-and-hold trading strategy with the exclusion of transaction costs. The results also indicate that the proposed system can outperform an existing portfolio allocation system in a financial institution, but the performance was not consistent over all considered time periods.

KEYWORDS: Fuzzy logic, technical analysis, trading system, genetic algorithm, portfolio allocation.

## 1 INTRODUCTION

Forecasting price movements in financial markets is an important activity for constructing portfolios to earn excess return. Traders try to exploit the information they receive from multiple sources by combining the information with the trading strategy that they follow. Usually, the trading strategy varies over time and the traders aim to adapt their strategies to changes in market conditions by learning from experience and other information. Although predictability of financial markets is the subject of an ongoing debate, most traders feel that the financial markets are not fully efficient and that there exist temporary "pockets of predictability", which could be exploited for realising excess returns above the market average [1]. Consequently, many financial institutions have developed decision support systems to help traders and analysts make their decisions more quickly and more effectively.

Technical analysis is sometimes used in financial markets to assist traders make buying and selling decisions. Technical analysis assumes that securities move according to trends and patterns that are sustained over (brief) periods of time until a change in the market condition activates another trend. The success of technical analysis depends, however, on how one interprets the available signals. Human expertise is thus important and, with more expertise, traders might be able to detect subtler changes in market trend and conditions. Decision support systems based on technical analysis often use only quantitative measures without an explicit link to the expertise of traders. Fuzzy systems have the potential to make this link. On one hand, a fuzzy system processes information numerically. On the other hand, the global behaviour of the system can be described with linguistic rules, which implies that the behaviour of the system can be specified in a manner more familiar for the traders. It may even be possible to design the system such that it mimics the reasoning and decision making process of a human trader using technical analysis, provided such information could be elicited from the traders.

In this study, we propose a fuzzy logic based trading system to predict price movements in the financial markets. The system is designed to distinguish various regimes in the market and generates a buy or sell signal for a trader who has to invest in a mix of European, American and Japanese bonds and currency. The structure of the fuzzy system is chosen such that it reflects the way experts of a financial institution reason about their trading decisions. Hence, expert knowledge was used as a guideline during the structure selection phase of the fuzzy system. Although, the signal from the system is meant primarily for a human trader, it can also be combined with a portfolio allocation mechanism to trade automatically. We study the performance of the system based on a couple of performance allocation strategies. The parameters of the fuzzy system are optimised by using a real-coded genetic algorithm. During training, the proposed system learns from past experience and adapts itself to changes and trends in the financial markets. The performance of the fuzzy system is compared with two other strategies as a benchmark. Two of the benchmarks follow a buy-and-hold strategy, while the third is an existing system at a financial institute, which uses a committee-of-experts approach for advising the traders.

The outline of the paper is as follows. We give, in Section 2, an overview of how fuzzy systems have been used in financial applications in the literature. We discuss, in Section 3 the background for technical analysis and several technical analysis indicators that are used in this study. The proposed fuzzy logic based trading system is described in Section 4. We discuss the optimisation of the parameters of the fuzzy system in Section 5 and study the performance of the system in Section 6. Finally, conclusions are given in Section 7.

## 2 FUZZY SYSTEMS IN FINANCE

Fuzzy systems have been widely used in expert systems, machinery, home appliances and robotics. Recently, applications in the finance field have also been reported, exploiting the ability of fuzzy systems to model the vague and imprecise information. Fuzzy systems have been used with various technical indicators in previous studies. Zhou and Dong [2] model the cognitive uncertainty incorporated in technical analysis by using a fuzzy-logic approach. Their algorithm has been able to offer superior precision in detecting and interpreting technical patterns over visual pattern analysis done by experts. Lin *et al.* [3] make use of a fuzzy system with KD technical index to predict stock indices. KD index is a stochastic oscillator, which consist of two lines namely K and D, where D is smoothed version of the K line. Their research shows that the returns generated with the fuzzy systems are significantly larger than linear regression models, neural networks and other investment strategies. Hiemstra [4] followed a similar approach with a fuzzy inference system, but with other indicators to predict the stock market. The results combining technical analysis and fuzzy logic were very promising.

Since different artificial intelligence methods have different strengths and limitations, hybrid systems have also been studied to obtain synergetic combinations of methods. Abraham and Nath [5] provides an overview of different hybrid models and architectures. In particular, combinations of fuzzy systems with neural networks and/or genetic algorithms appear to be popular in real-world implementations. A neuro-fuzzy system to predict financial time series is described in [6]. The prediction of stock and option prices of the S&P and Dow Jones indices have been examined, which resulted in profitable trading strategies. The results from the paper show the potential of neuro-fuzzy modelling for finance and management. Neuro-fuzzy models have also been used to predict other time series such as the Greek manufacturing index [7] and Korea stock price index [8]. They have also been applied for portfolio evaluation [9]. Hybrid combinations of fuzzy and probabilistic systems have also been proposed. For example, van den Berg *et al.* analyse a financial market by using a probabilistic fuzzy model [10], in which linguistic uncertainty is combined with probabilistic uncertainty.

The problem of finding desirable fuzzy rules is a very important process in the development of fuzzy systems. In practice, acquiring the rules from experts only is quite a difficult task. Alcalá *et al.* [11] give an overview of different approaches of learning and tuning of a fuzzy system. Herrera *et al.* [12] propose a method to learn the rules from examples (input-output data) using a genetic algorithm. Mohammadian and Kingham [13] developed a hierarchical fuzzy logic system using genetic algorithm to predict the interest rates in Australia. Using a genetic algorithm as a training method for learning the fuzzy rules, the number of rules could be reduced significantly, resulting in more efficient systems. The results show that the system is able to give accurate prediction of the interest rates.

In the following, we describe a fuzzy system to predict market price movements for investing in portfolio of European, American and Japanese bonds and currency. The system has been developed with participation of traders and experts from a financial institution, whose knowledge formed a constraint on the design of the structure of the fuzzy system. The system takes a number of technical analysis indices as input, which have been specified by traders. The system generates a buy or sell signal, but it can also be combined with portfolio allocation mechanisms for automated trading. Below, we first discuss technical analysis and the indices that the proposed fuzzy system uses.

# 3 TECHNICAL ANALYSIS

Technical analysts seek patterns, trends and other factors in price series, which may predict a stock's future performance and then make buy/sell decisions based on those factors. These factors are usually defined as indices derived from historical data following a particular kind of reasoning, which is usually based on experience or heuristics. Although there is a controversy about the effectiveness of technical analysis, various studies have reported that technical analysis of historical prices possesses predictive power, beating buy-and-hold strategies and other (statistical) methods [14], [15], [16]. Smirlock and Starks [17] show that there is a relation between trading volume and past returns, and state that past trading volume may contain valuable information about a security's price. Hiemstra and Jones [18] found evidence of nonlinear causality between returns and volume by testing the daily returns of the Dow Jones index and with the trading volumes of the NYSE. Fama and French [19] found evidence of mean reversion for stock prices in the long run claiming that stock prices are predictable in the long run.

For the purpose of this paper, the domain expertise was provided by the experts of a financial institution. The experts were already using a trading system (called TS hereafter) to assist them in their decisions. This system uses technical analysis as its input. Based on the working of this system and their experience, four technical indices were identified as having predictive power. These were Commodity Channel Index (CCI), Relative Strength Index (RSI), Moving Average Convergence and Divergence (MACD) and the Bollinger Band. Below, we describe each of these indices briefly.

## 3.1 Moving Average Convergence/Divergence (MACD)

Moving Average Convergence/Divergence is an oscillator intended as an improvement on the simple moving average approach. It generates its signal from the crossing of moving average lines [20]. The MACD line is calculated by taking two exponentially moving averages of closing prices with different periods and subtracts the moving average with the longer period from the one with the shorter period. The MACD is a centred oscillator line, which fluctuates above and below zero, without any limits. Usually, 12/26 MACD is used, which computes the difference between the 26-day and the 12-day exponential moving averages. The crossing of *signal line* is usually used to indicate a buy or sell signal. The signal line is usually itself a 9-period exponential average of the MACD line. The trading rules for the MACD are summarised as follows.

1. IF MACD is above the signal line THEN BUY.
2. IF MACD is below the signal line THEN SELL.

## 3.2 The Commodity Channel Index (CCI)

The Commodity Channel Index (CCI) is originally designed to identify cyclical patterns in commodities [20]. The underlying assumption behind the index is that commodities (stocks, bond) have high and low values at periodic cycles, and it tries to estimate when an asset is oversold or overbought. The CCI boundaries are often considered between $-100$ and $+100$ (or sometimes between $-200$ and $+200$). When the CCI is above $+100$, the asset is considered to be overbought. Similarly, if the CCI falls below $-100$, the asset is considered to be oversold.

CCI is computed by using an asset's *typical price* (TP), which is the average of its high, low and closing prices on a day. Then, the moving average of the typical price for $N$ periods is computed ($\mathrm{MATP}$). Next, the mean deviation $\mathrm{MD}$ is computed by taking the average difference between typical prices in the $N$-day period and the last period's smoothed typical price, i.e. moving average of the typical price. The CCI is then defined as

$$\mathrm{CCI} = \frac{\mathrm{TP} - \mathrm{MATP}}{c \times \mathrm{MD}}, \tag{1}$$

where the constant $c$ is usually chosen to be $0.015$. The market classification rules with the CCI are as follows.

1. IF CCI increases to above $100$ THEN BULLISH.
2. IF CCI decreases to below $100$ THEN BEARISH.
3. IF CCI increases to above $-100$ THEN BULLISH.

4. IF CCI decreases to below $-100$ THEN BEARISH.

### 3.3 Relative Strength Index (RSI)

The relative strength index also considers whether an asset is overbought or oversold. It is computed as

$$\mathrm{RSI} = 100\frac{\mathrm{RS}}{1+\mathrm{RS}}, \tag{2}$$

where $\mathrm{RS}$ is the ratio of total positive returns to the total negative returns in the last $N$ periods. The crossing boundaries for generating the signals are rather arbitrary, but we have used the following classification rules.

1. IF RSI increases to above 70 THEN BULLISH.
2. IF RSI decreases to below 70 THEN BEARISH.
3. IF RSI increases to above 50 THEN BULLISH.
4. IF RSI decreases to below 50 THEN BEARISH.
5. IF RSI increases to above 30 THEN BULLISH.
6. IF RSI decreases to below 30 THEN BEARISH.

### 3.4 Bollinger Bands

The Bollinger Bands method compares volatility and relative price levels over a period of time. The volatility is measured as standard deviation of the security prices. The three signals of this technical indicator forms a band that covers the time series. The middle line of the Bollinger Bands is computed by taking the $N$-period moving average of the price series. The upper line of the Bollinger band is then at distance $c\sigma$ from the middle line, while the lower line is at a distance $-c\sigma$, where $c$ is a positive constant and $\sigma$ is the standard deviation computed over a moving window of $N$ periods. The market classification rules used with the Bollinger Bands are the following.

1. IF Price increases to above Bollinger upper line THEN BULLISH.
2. IF Price decreases to below Bollinger upper line THEN BEARISH.
3. IF Price increases to above Bollinger middle line THEN BULLISH.
4. IF Price decreases to below Bollinger middle line THEN BEARISH.
5. IF Price increases to above Bollinger lower line THEN BULLISH.
6. IF Price decreases to below Bollinger lower line THEN BEARISH.

Technical analysis is open to different personal interpretations. Success depends on how well one can interpret the indicators. A decision support system based on technical indicators should therefore mimic the behaviour of human decision makers in some sense. Fuzzy set theory provides formal mechanisms for approximate reasoning that could be used for reasoning with subjective and vague information. In the next section we describe a trading system based on fuzzy logic.

## 4 FUZZY LOGIC BASED TRADING

The fuzzy trading system is roughly based on the types of rules mentioned in Section 3. In general, the rules with crisp thresholds are replaced by rules with fuzzy thresholds. The implementation is made as a Mamdani Fuzzy Inference System (FIS). The output of the system is a buy or sell signal. Hence, the system predicts a price trend to step in and step

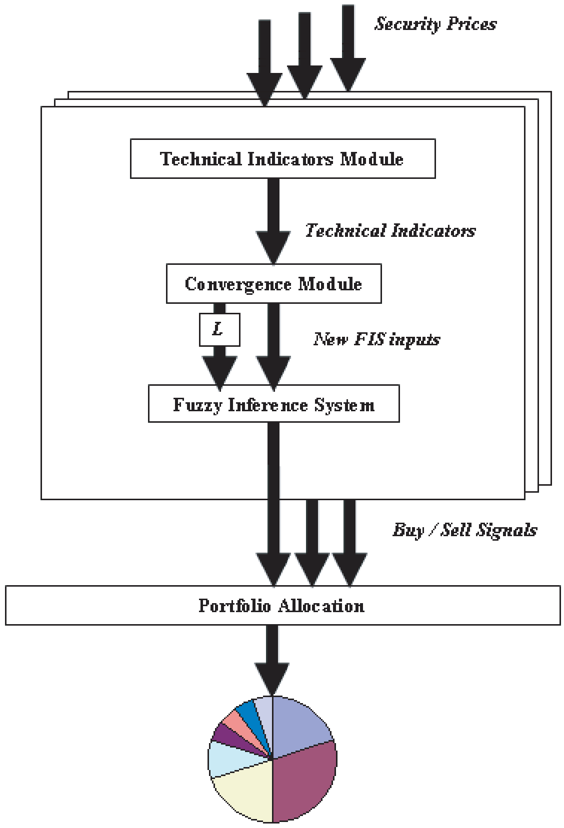


Figure 1: Architecture of the fuzzy logic based trading system.

out of the market of a security. Finally the different buy and sell recommendations for different securities are turned into a portfolio allocation depending on the strategy used. Short selling is prohibited. Consecutive periods of buy or sell signals in which the recommendation does not change are considered a 'hold' period, implying that the investor should stay in or out of the market, respectively. The proposed trading system consists of six modules, as illustrated in Figure 1. Below, we discuss each module in more detail.

### 4.1 Technical Indicators Module

The input to the system is the time series of the securities with weekly frequency. This input enters the technical indicators module, which calculates from each time series, the four technical indicators, namely MACD, RSI, CCI and Bollinger Bands. Following expert knowledge regarding these technical indicators, the MACD indicator looks for bullish and bearish market movements and is a lagging indicator. The RSI indicator belongs to the category of oscillators, and it seeks the security price momentum. The CCI does not make any up or down trend recommendation, but quantifies how strong the current trend is, either going up or down. The Bollinger bands compare the volatility with the price levels.

The parameters for the technical indicators are specified according to the default guidelines in technical analysis. For the MACD indicator, 26 and 12 weeks are used as the long-term and the short-term moving average, respectively. The trigger line for the MACD is the 9 weeks moving average of the MACD. The RSI indicator uses a period of 20 weeks. Similarly, the CCI indicator uses a 20 week period and $c = 0.015$. The Bollinger bands are calculated using a 20 week moving average for the middle band and a constant of $2\sigma$ for the upper and lower bands, respectively. The outputs of the Bollinger band consist of three series, namely that of the middle, lower and upper bands, while the other technical indicators produce only one output. Table 1 summarises the parameters used in the technical indicators module.

Table 1: Technical indicator parameters.

| Technical Indicator | Parameters |
|---|---|
| MACD | Long = 26<br>Short = 12<br>Trigger = 9 |
| CCI | N = 20<br>C = 0.015 |
| RSI | N = 20 |
| Bollinger Bands | N = 20<br>C = 2 |

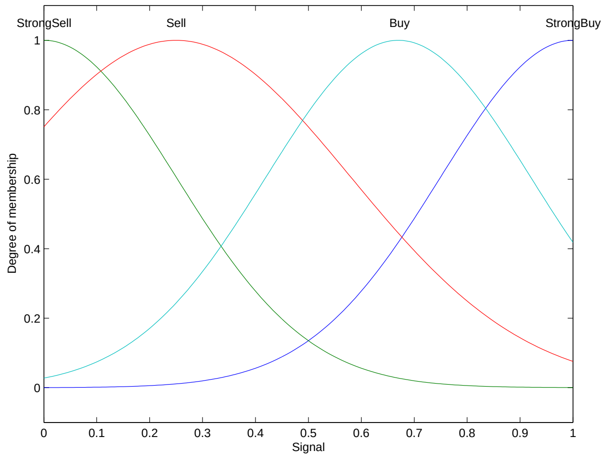


Figure 2: Membership functions defined on the output domain.

### 4.2 Convergence module

The convergence module transforms the technical indicators into new auxiliary variables so that they are used as inputs for the fuzzy inference system. For example, the difference between the MACD signal and the trigger signal is computed and used as input to the fuzzy system. Some indicators lead to multiple inputs to the fuzzy system. For example, three inputs for the fuzzy systems are generated from the technical indicator RSI, namely the distance to the upper bound, the distance to the lower bound and the distance to the middle line. Similarly, the CCI and the Bollinger bands are mapped into 17 new variables acting as inputs to the fuzzy inference system.

### 4.3 Fuzzy inference system (FIS) module

The fuzzy inference system (FIS) module takes the outputs of the convergence module and generates a trading signal based on the rules defined in the rule base. The system is a Mamdani fuzzy system. Gaussian membership functions are used both in the inputs and in the output. Two membership functions have been defined for each of the inputs. The output of the fuzzy system is a signal on a normalised domain, on which four different fuzzy sets, STRONG SELL, SELL, BUY, STRONG BUY are defined. The partitioning for the output domain is shown in Figure 2. A strong buy signal is generated when the output is close to 1.0 and a strong sell signal is generated when the output is close to zero. The centers of the membership functions are distributed evenly over the domain.

The system uses max-min reasoning. Minimum operator is used for aggregating the rule antecedents. Largest of the maximum (LOM) method is used for defuzzification. In order to classify the output into one of the four conditions, the output with the largest membership is selected. If there are multiple output values with the same maximal membership value, the largest output value is used as the defuzzified output.

### 4.4 Rule Base

The rule base of the fuzzy inference system is initialised following the technical analysis guidelines for the four technical indicators used in the model. In this context, MACD is used in all the rules. The initial rule base is constructed with two technical indicators producing the following 12 fuzzy rules.

Rule 1: IF $\text{MACD}_f$ is low and $\text{RSI}_{upper_t}$ is low and $\text{RSI}_{upper_{t-1}}$ is high THEN SELL
Rule 2: IF $\text{MACD}_f$ is low and $\text{RSI}_{middle_t}$ is low and $\text{RSI}_{middle_{t-1}}$ is high THEN STRONG SELL
Rule 3: IF $\text{MACD}_f$ is high and $\text{RSI}_{middle_t}$ is low and $\text{RSI}_{middle_{t-1}}$ is low THEN STRONG BUY
Rule 4: IF $\text{MACD}_f$ is high and $\text{RSI}_{lower_t}$ is low and $\text{RSI}_{lower_{t-1}}$ is low THEN BUY
Rule 5: IF $\text{MACD}_f$ is low and $\text{CCI}_{upper_t}$ is low and $\text{CCI}_{upper_{t-1}}$ is high THEN STRONG SELL
Rule 6: IF $\text{MACD}_f$ is high and $\text{CCI}_{upper_t}$ is high and $\text{CCI}_{upper_{t-1}}$ is low THEN BUY
Rule 7: IF $\text{MACD}_f$ is low and $\text{CCI}_{lower_t}$ is low and $\text{CCI}_{lower_{t-1}}$ is high THEN SELL
Rule 8: IF $\text{MACD}_f$ is high and $\text{CCI}_{lower_t}$ is high and $\text{CCI}_{lower_{t-1}}$ is low THEN STRONG BUY
Rule 9: IF $\text{MACD}_f$ is high and $\text{BB}_{upper_t}$ is low and $\text{BB}_{upper_{t-1}}$ is high THEN STRONG SELL
Rule 10: IF $\text{MACD}_f$ is high and $\text{BB}_{middle_t}$ is high and $\text{BB}_{middle_{t-1}}$ is low THEN BUY
Rule 11: IF $\text{MACD}_f$ is high and $\text{BB}_{middle_t}$ is low and $\text{BB}_{middle_{t-1}}$ is high THEN SELL
Rule 12: IF $\text{MACD}_f$ is high and $\text{BB}_{lower_t}$ is high and $\text{BB}_{lower_{t-1}}$ is low THEN STRONG BUY

### 4.5 Asset allocation module

The fuzzy system is primarily designed for generating a buy or sell signal. However, it is also possible to use the system directly for trading purposes. This is achieved by using an *asset allocation module* placed behind the FIS module. The performance of the system can also be quantified in this way, by observing the returns generated by the system compared to other alternatives.

The investment strategy that is followed is to primarily allocate all of the money into Europe, US and Japan. This is done by investing on index futures of MSCI US, EMU and JPN. Index futures are traded in terms of number of contracts. Each contract is to buy or sell a fixed value of the index multiplied by the specified monetary amount. The position is adjusted according to market value on a daily basis. A margin account is setup to reflect the daily gains or losses depending on the investor's future position. For example, when a long position on a future index position is taken with a spot price of $K$ and the index price is $S_T$ the payoff will be $R_T = S_T - K$. For simplicity, it is assumed that the futures price and the index move in a one to one relationship. Another important aspect of index futures is that the contracts are always settled in cash, meaning that it is impossible to make actual delivery of the index. The difference between the cash and the futures index on the date of settlement is the profit (loss) for the investors.

**Single asset allocation.** The trade orders are executed according to the signals generated by the fuzzy system. The different buy and hold signals must be transformed into portfolio weights. For STRONG SELL signal, the asset position is entirely sold off, holding only money and no futures contracts. The allocation for that particular asset in this case is zero. When a SELL signal is generated, only 75% of the assets are sold off from its current value. The same also applies for the BUY signals. Only 75% of the cash is allocated in case of a BUY signal and 100% of the cash is allocated in case of a STRONG BUY signal.

Note here that STRONG SELL or SELL signals can only be executed when the asset position from the previous period is not zero. For this strategy it is not possible to go short, implying that it is not possible to sell what you do not already own. Another important aspect is that no allocation takes place when the current signal is the same as the previous signal. This can be seen as a 'HOLD' period.

**Equally weighted portfolio.** When there are multiple assets to invest in, a portfolio allocation strategy is needed, as single asset allocation is not sufficient in that case. To form a portfolio which consists of different asset classes with different signals, the allocation strategy must be extended. One possible strategy is based on the principle of equally weighted allocation. If no positive trend can be found in the MSCI indices, the money is allocated in the money markets in US or EMU bonds, or in US and JPN CASH account. When there is no positive trend found in the money market, the money is deposited in an EUR CASH account.

For portfolio allocation the idea is to look at the sell signals at time period $t$ first, and adjust the existing portfolio weights based on these signals. Afterwards, another reallocation takes place based on the buy signals, making sure at the end that all weights sum up to one. In the beginning, when there are no assets, the sell signals are treated as zero allocations. The subsequent allocations depend on the generated signals and the previous allocations. When different buy and strong buy signals are present at time $t$, which corresponds to 75% and 100% allocations respectively, the weights are normalised. If only BUY signals are present, the weights are divided equally amongst the respective asset classes.

**Value weighted portfolio.** The second portfolio allocation strategy is the value weighted approach. The allocation principle is the same as that of equally weighted, but more weights are given to Europe and US markets when SELL or STRONG SELL signals occur relative to Japan. In our case, we have chosen to invest twice the amount in Europe and US compared to that invested in Japan. This is only the case for the MSCI indices and not for the bond and CASH market.

## 5 PARAMETER OPTIMISATION

In order to improve the accuracy of the fuzzy inference system, we used a genetic algorithm (GA) to optimise the parameters of the input and output membership functions. Other hybrid approaches are possible, such as neural networks, but the disadvantage is that the solution might be trapped in a local optima. Furthermore, GA optimisation allows the use of more flexible and general fitness functions than is generally possible with neural networks. Also, a GA optimiser can be extended more easily in the future to optimise the rule base. In that case, genetic algorithms have the advantage, as they have the ability to efficiently search a large solution space and escape from local optima.

The selection process of the genetic algorithm uses tournament selection. Under tournament selection two individual are randomly selected from the population and the one with the best fitness is selected for the crossover phase. We have used single point crossover and arithmetic crossover in this study. The crossover probability was 0.8. Chromosome underwent mutation with a mutation probability of 0.2. Mutation consisted of modifying part of the chromosome at a randomly selected location. The elitism parameter is set to 1, meaning that the best fitness individual of one generation is transferred to the next generation.

Since Gaussian membership functions are used, there are two parameters for each membership function. The centres of the membership functions have been fixed at the edges of the domain of the variable. Hence, only the spreads of the membership functions are optimised. Since there are 17 input variables to the system and two fuzzy sets are defined for each variable, the chromosome consists of 34 parameters that are optimised. The values of the parameters are real numbers and therefore a real-valued coding scheme is used for the genetic algorithm. The genetic algorithm starts off by creating an initial population. The population size is 100. The algorithm is run for 200 generations. The encoding is selected such that each parameter is positive (since the spread cannot be zero or negative) and its value is constrained from the above by the boundary of the extremes of the input data. Hence, the parameter values lie within the domain of discourse of the variable.

The fitness function is defined as the average return generated when the system trades over a number of instances of the data set. A sliding window approach is used for this purpose. A FIS in the population is used to trade over the given window of price values. It is assumed that the system starts with 100 units of cash and no shares. Based on the signals generated by the fuzzy system, buy and sell orders are processed within the sliding window. When a sell condition occurs the system shorts the shares only if the shares are non zero. It is not possible to sell what you do not own. The system goes long if a buy recommendation is generated by purchasing more shares under the constraint that the cash position is non zero. At the end of the window, the position is closed holding only cash and no shares. Average returns within the considered window are used as the fitness associated with that particular window. The overall fitness of the solution is calculated as the average fitness over all sliding windows that are considered.

## 6 PERFORMANCE ANALYSIS

The performance of the system has been studied by using financial market data collected in the period 1997 to 2006. The data used are weekly closing prices of the indices MSCI EMU, MSCI US, MSCI Japan, EMU Bonds, US Bonds, US CASH, EURO CASH and Japan CASH collected from the Bloomberg database in the period of 20/4/1997 to 20/4/ 2006. Thus, a total of 485 data points was available for the analysis. The MSCI indices indicate the Daily TR Gross index of Europe, US and Japan. The Bond indices are designed as a transparent benchmark for government bond markets. The

Table 2: Data sets used in the experiments.

| Period | Nr Training points | Nr Testing points |
|---|---|---|
| 09/01/1997 - 20/04/2006 | 406 | 44 |
| 20/04/2000 - 20/04/2006 | 252 | 27 |
| 22/04/1999 - 21/04/2005 | 252 | 27 |
| 24/04/1998 - 22/04/2004 | 252 | 27 |
| 24/04/1997 - 24/04/2003 | 252 | 27 |

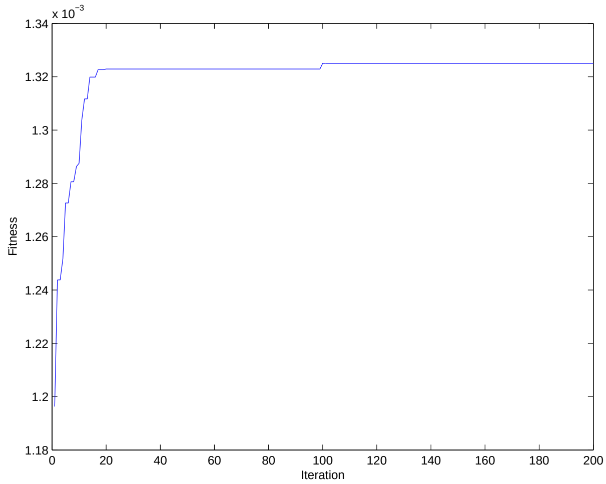


Figure 3: Example of fitness evolution.

EMU Bonds 10+ represents the Merrill Lynch Global Index and the US Bonds 10+ is the Bloomberg/EFFAS US Bond Index. The CASH indices correspond to the City Group 3 months Deposit. Considering the fact that the data are collected in their own specific currency, they are converted into a single currency, which was the EURO in this study.

The data set is subsequently divided into a training data set to determine the parameters of the model and a testing data set for the validation of the model. The training data consist of 90% of the total data set. The other 10% of the data set is used for out of sample testing with the optimised fuzzy inference system. In order to assess the robustness of the model to different realisations of the price series, we have also split the data set into five different groups, each comprising a trading period of six years. Table 2 summarises the different time periods used and the amount of training and testing data points in the data subsets. Note that after dividing the data set into smaller periods, the length of the training period and the testing period decreases, too.

The GA has been run for 200 generations at each time to optimise the parameters of the fuzzy system. This number has been found to be sufficient to converge. Figure 3 shows the evolution of the fitness value of the best individual in the population in a typical run of the system.

The performance of the system is studied with the equally weighted and the value weighted portfolio strategies. The performance from these portfolios that were constructed based on the advice from the fuzzy system is compared with that of other portfolios that use different trading strategies. The first benchmark portfolio is one from a financial institution's current trading system TS. The second benchmark portfolio is the equally weighted buy-and-hold portfolio based on investing on only three indices namely the MSCI EMU, MSCI US and MSCI JPN. The weights are calculated in the first period and they are not changed for the whole out-of-sample period. The portfolio value is tracked during this period. The weights $w_i$ for asset $i$ are calculated as

$$w_i = \frac{100}{3 \times P_i}, \tag{3}$$

for an initial investment of 100. In (3) $P_i$ denotes the price of security $i$ at the start of the out-of-sample period. Finally, the third benchmark portfolio is an equally weighted allocation amongst the eight different securities considered in this study, adding more diversity in the portfolio, therefore lowering the overall risk in comparison with the second benchmark portfolio. The initial weights are again calculated using the formula (3), but they are adjusted according to the increased number of assets.

Table 3: Portfolio Profit and Returns

| Period | | $\text{FIS}_{\text{EQUAL}}$ | $\text{FIS}_{\text{VALUE}}$ | TS | BENCHMARK 1 | BENCHMARK 2 |
|---|---|---|---|---|---|---|
| 1997-2006 | Profit | 25.90 | 23.40 | 16.16 | 24.59 | 6.67 |
| | Annual Return | 28.43% | 25.94% | 18.48% | 27.16% | 8.00% |
| | Annual Stdev | 10.18% | 9.65% | 8.37% | 10.16% | 6.13% |
| | Sharpe ratio | 2.50 | 2.38 | 1.85 | 2.38 | 0.82 |
| 2000-2006 | Profit | 18.30 | 17.62 | 15.66 | 18.47 | 5.18 |
| | Annual Return | 34.11% | 32.89% | 29.53% | 34.42% | 10.27% |
| | Annual Stdev | 9.07% | 8.41% | 8.46% | 9.23% | 5.89% |
| | Sharpe ratio | 3.43 | 3.55 | 3.14 | 3.40 | 1.23 |
| 1999-2005 | Profit | 5.25 | 5.21 | 3.34 | 4.03 | 2.06 |
| | Annual Return | 10.72% | 10.62% | 6.80% | 8.38% | 4.29% |
| | Annual Stdev | 9.98% | 9.69% | 6.74% | 9.93% | 6.62% |
| | Sharpe ratio | 0.77 | 0.79 | 0.56 | 0.54 | 0.19 |
| 1998-2004 | Profit | 14.53 | 14.78 | 3.79 | 14.15 | 5.89 |
| | Annual Return | 28.46% | 28.68% | 8.04% | 27.57% | 11.75% |
| | Annual Stdev | 16.11% | 14.60% | 11.09% | 14.61% | 7.71% |
| | Sharpe ratio | 1.58 | 1.76 | 0.45 | 1.68 | 1.13 |
| 1997-2003 | Profit | -17.55 | -15.77 | 2.33 | -9.65 | -5.43 |
| | Annual Return | -36.82% | -32.63% | 4.66% | -18.70% | -10.92% |
| | Annual Stdev | 18.25% | 18.03% | 3.30% | 18.01% | 6.99% |
| | Sharpe ratio | -2.18 | -1.98 | 0.50 | -1.20 | -1.99 |

The Sharpe ratio ($S_r$) is used as a measure of the overall portfolio performance over the out-of-sample period. The Sharpe ratio measures the average return per unit risk. The formula for the Sharpe ratio looks like as follows,

$$S_r = \frac{E(R_p - R_f)}{\sigma_p} \tag{4}$$

where $R_p$ and $\sigma_p$ denote the average return and the standard deviation of the portfolio over the out of sample period, respectively. In (4), $R_f$ is the risk free interest rate and is set for this experiment at 3%. The experiment is conducted under a risk neutral environment.

The portfolio performance for the different out-of-sample periods are shown Table 3. The results show that the portfolio constructed by the fuzzy trading system is able to outperform TS and also both the buy-and-hold portfolios in the first four testing periods. This can be seen from the profit and the Sharpe ratio in these periods, which are higher in most cases than that of the benchmarks.

When we compare the equally weighted portfolio with the value weighted portfolio, it seems that the equally weighted portfolio produces more risky returns than the value weighted approach. Consequently, the returns of the value weighted portfolio are in general worse. Looking at the Sharpe ratio of the different period, we observe that the value weighted approach have a small advantage as indicated by the more favourable Sharpe ratio value in most of the periods considered.

In the last sample set (1997–2003), the fuzzy trading system fails to outperform TS and other benchmarks. This can be observed from the negative returns that the portfolios produce in this sample period. Hence, the performance of the fuzzy system is not consistent over all trading windows. Following the trading advice from the fuzzy system leads, in this trading window, to a loss. From Table 3 it can be seen that the returns from TS are positive, also in this period. Most likely, this is due to the portfolio allocation mechanism. TS uses more complicated mechanisms for portfolio allocation than the simple equally weighted or value weighted approaches that we have used together with the fuzzy system. The result is that TS is more risk averse. Although it performs well in this period too, its returns are in general lower than the fuzzy system returns in other trading periods considered.

## 7 CONCLUSIONS

We have proposed a fuzzy logic based trading system for finding trends in financial indices and generating trading advice for the traders. The fuzzy system used information derived from technical analysis indices as input. It was designed to mimic human behaviour in interpreting technical indicators. By using the different technical indicators as inputs, a flexible system is built. The membership functions of the fuzzy system are optimised by using a genetic algorithm.

The portfolios constructed based on the trading advice from the fuzzy system outperforms the buy-and-hold portfolio trading strategies and also a system currently in use at a financial institution on many occasions. However, we have not found the performance of our system to be consistently better in all trading periods that we have tested. While the portfolio produced by the proposed system outperforms the benchmark portfolios in four of the five tested trading periods in terms of risk-discounted returns measured by the Sharpe ratio, it leads to losses in one trading period. The current system in use at the financial institution is able to deliver positive results in all trading periods we have tested. We think that this is related to the better portfolio allocation mechanism of the system, diversifying risks, while our proposed system used a simple portfolio allocation mechanism of equal weighting.

The added value of the fuzzy system is that it uses a strategy that experienced traders use to recognise patterns in financial indices. Hence, it fits well to the perception of the traders. However, humans usually use a variety of strategies, switching from one to the other depending on context, circumstances and external information. More research is needed to provide the system with such extended flexibility. Future research should concentrate on bringing about this additional flexibility by optimising *e.g.* the fuzzy rule base and implementing a better risk control mechanism when allocating the portfolios.

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