Evolutionary Algorithms in Optimization of Technical Rules for Automated Stock Trading

by

Harish K Subramanian

Thesis

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Master of Science in Engineering

The University of Texas at Austin

December 2004

Evolutionary Algorithms in Optimization of Technical Rules for Automated Stock Trading

Approved by
Supervising Committee:

Peter Stone

Benjamin Kuipers

Joydeep Ghosh

Dedicated to

Jacks of All Trades

Acknowledgements

I would like to express my deep gratitude to Dr. Peter Stone for his guidance, advice, and encouragement. It has been great fun and a privilege to conduct research under his supervision. I am grateful to him for the confidence he had in me.

I would also like to thank Dr. Benjamin Kuipers and Dr. Joydeep Ghosh for their support.

I would like to thank Subramanian Ramamoorthy for providing support and interesting discussion. I would also like to express my gratitude to family and friends for their encouragement and support.

Abstract

Evolutionary Algorithms in Optimization of Technical Rules for Automated Stock Trading

Harish K Subramanian, MSE

The University of Texas at Austin, 2004

Supervisors: Peter Stone, Benjamin Kuipers

The effectiveness of technical analysis indicators as a means of predicting future price levels and enhancing trading profitability in stock markets is an issue constantly under review. It is an area that has been researched and its profitability examined in foreign exchange trade [1], portfolio management [2] and day trading [3]. Their use has been advocated by many traders [4], [5] and the uses of these charting and analysis techniques are being scrutinized [6], [7]. However, despite their popularity among human traders, a number of popular technical trading rules can be loss-making when applied individually, typically because human technical traders use combinations [8], [9] of a broad range of these technical indicators. Moreover, successful traders tend to adapt to market conditions by varying the weight they give to certain trading rules and dropping some of them as they are deemed to be loss-making. In this thesis, we try to emulate such a strategy by developing trading systems consisting of rules based on combinations of different indicators, and evaluating their profitability in a simulated economy. We propose and empirically examine two schemes, using evolutionary algorithms (genetic algorithm and genetic programming), of optimizing the combination of technical rules. A multiple model approach [10a] is used to control agent behavior and encourage unwinding of share position to ensure a zero final share position (as is essential within the framework that our experiments are run in). Evaluation of the evolutionary composite

technical trading strategies leads us to believe that there is substantial merit in such evolutionary designs (particularly the weighted majority model), provided the right learning parameters are used. To explore this possibility, we evaluated a fitness function measure limiting only downside volatility, and compared its behavior and benefits with the classical Sharpe ratio, which uses a measure of standard deviation. The improved performance of the new fitness function strengthens our claim that a weighted majority approach could indeed be useful, albeit with a more sophisticated fitness function.

Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

The stock market represents an interesting dynamical system that intrigues researchers from a number of disciplines including the machine learning community which aims to build autonomous agents as part of a larger body of research into autonomous agent systems [11]. Autonomous trading in stock markets is an area of growing interest in the academic as well as commercial circles. Various attempts at forecasting and prediction of time series data including neural network prediction schemes have been moderately successful in the *prediction* of prices based on complex mathematical models [12], [13]. While these are rigorous and expansive schemes to base trading on, and despite their capability of producing good results when modeled right, the fact remains that developing a sufficiently expansive model is a very difficult challenge. As long as profitability is our primary concern, the goal remains to try and produce productive and profitable strategies, even if they are specific to a market. We aim to utilize existing intuition and combine 'conventional wisdom' with computational techniques to try and improve profitability.

1.1 MOTIVATION

The stock market is a time varying, highly volatile process with so many factors affecting its variation that it is very difficult to model its behavior with any precision. Numerous investigations have been largely unsuccessful in predicting its behavior, failing to produce substantial returns over basic, intuitive "reactionary" rules [14], [15]. In fact, a controversial but oft cited investment theory known as the *Efficient Market Hypothesis* [16] implies that it is impossible to beat the market. In other words, it suggests that the behavior of share price variation in the stock market does not contain much predictable behavior that can be taken advantage of to ensure profitability. Other studies also conclude that the autocorrelation for day to day changes is very low [17] and that the process behaves very much like a random walk [18]. However, in the technical trading community, the popular belief is that such an assumption would mean that someone with no knowledge of the market making a random trade is about as likely to

succeed as an experienced trader. Deferring to intuition, they argue that this is not the cases, and claim that there are some non-random aspects of the market that can be exploited to trade profitably [6].

There is now substantial interest and possible incentive in developing automated programs that would trade in this market much like a technical trader would, and have it be relatively autonomous. Unless the market does not move at all during a trading day, there is always some strategy that would work *on a given day* to make a lot of money. These strategies would then lose money on other days, when a degenerate *do nothing* strategy would have been a better way to go. We may think of a 'successful strategy' to be one that maximizes the number of profitable days, as well as has positive average profits over a substantial period of time, coupled with reasonably consistent behavior. What does it mean to be 'consistent'? And what is a substantial period of time? In the context of our experiments in this thesis, we examine these questions in later sections. Further discussion of evaluation criteria for our strategies can be found in Chapter 2. In this thesis, we aim to study the effect of combining multiple 'intuitive' trading rules within the framework of the *Penn Lehman Automated Trading* (PLAT) *project* [19]. There have been numerous studies on the use of technical trading strategies in intraday stock trading. Even with exhaustive optimization of parameters, most of these strategies have often proved too simplistic and coarse to utilize the variation of high frequency stock price variation [20], [21].

A possible solution is to combine these individual strategies much like a human trader would do on the floor of the stock exchange. Where the trader would rely on combining intuition and experience to make a final decision, the strategy we wish to test here is to emulate this behavior by using a genetic algorithm to tune the relative merits of the individual rules. In this thesis, we aim to verify the validity of a scheme of operation wherein the automated agent trades based on a combination of signals it receives from the various 'simplistic' rules. We explore two schemes of combining rules – adding weights to the various trading suggestions and adding or deleting certain rules altogether.

The two main contributions of this thesis are as follows. First, we propose that technical indicators, although useful, are not as profitable when used alone, as they are when used in conjunction with other technical trading rules. We explore two schemes of combination of technical trading rules, using evolutionary algorithms (Genetic Algorithm and Genetic Program) to optimize the combination of these rules, and conjecture that it would work better than an ad-hoc combination. We develop agents with a weighted majority design as well as one with provision for adding/deleting rules and the use of Boolean operators as combining elements. Second, we look at improvements in fitness functions for the evolutionary algorithms, so the model evolved by them are suited to days of different price dynamics and increase profitability over days of all kinds of behavior. To this end, we compare and contrast two different (but related) fitness functions, and the performance of the resulting agents. Finally, we aim to present an empirical study of performance of certain agent designs in controlled but fairly realistic market simulations in an effort to explore possible vistas in profitable automated agent development.

1.2 OUTLINE

The thesis aims to study the design, development and performance of an automated trading strategy utilizing a composite technical trading strategy optimized by a genetic algorithm. We also use a multiple model approach to control trading order placement based on share position of the agent. Trading simulations and controlled experiments are conducted to study the performance of this agent as well as its components.

The rest of the thesis is organized as follows. Chapter 2 delves into some details about the domain in which simulations are performed, background work and requisite terminology. We also briefly touch upon the design of other agents we use in our tests. Chapter 3 discusses the component technical trading strategies, as well as how they are composed. A brief introduction to aspects of genetic algorithm and genetic programming

optimization used in our strategy, along with some implementation issues, are also included. Chapter 4 contains a summary of experiment design, tests and simulations that were performed as well as the results and includes an analysis of the results. Finally Chapter 5 summarizes key results and a limitation of the work described in the thesis, and discusses some ideas for future work in the area.

Chapter 2. Background and Related Work

2.1 BACKGROUND

In this section, we review some of the earlier work done by researchers in the area. We also introduce basic trading concepts and discuss simulated trading environments including the one used for experiments throughout this thesis.

2.1.1 Literature Survey

Stock markets have been around for centuries and the classic 'scream' across the floor has been the medium of choice. Of late, however, markets have gone electronic. NASDAQ is a distributed trading system completely run over networks of computers. It allows customers' offers to be displayed on NASDAQ by their brokers or through ECNs (Electronic Crossing Networks). ECNs such as Island [22] allow customers to display their orders as well as trade orders with each other. Of course, trading in these markets on an experimental basis is a costly exercise not only due to the transaction fees, but the potential for steep penalties in the event of mistakes when a large amount of money is risked. Additionally, experimentation to verify effects such as that of volume of trade on profitability may involve high risks, as the downside to high volume trades is potentially very high.

The factors described above warrant the use of trading simulators. These range from in-class simulators, aimed at students to teach them the nuances of financial markets [23], and financial simulators for exam preparation [24] to advanced market models like the Santa Fe Artificial Stock Market [25]. However, various shortcomings of these and other such simulators (like the failure to simulate a realistic market scenario and failure to accommodate trading frequencies suitable to intra-day trading) have been addressed by the PLAT domain. It uses real-world, real-time stock market data available over modern ECNs and incorporates complete order book information; simulating the effects of

matching orders on the market. It also provides numerous APIs that allow the participants to program their own strategies and trade with other agents as well as the external market.

Technical Analysis has a long history among investment professionals. However, it has been approached with a great deal of skepticism in academia, over the past few decades, largely due to the belief in the efficient market hypothesis. Though this field has remained marginalized in literature, the accumulating evidence against the efficiency of the market [21] has caused a resurgence of interest in the claims of technical analysis as the belief that the distribution of price dynamics is totally random is now being questioned. These techniques assume that, notwithstanding the efficient market hypothesis, there exist patterns in stock returns and that they can be exploited by analysis of the history of stock prices, returns and other key indicators. [6] provides details on technical analysis for stock trading. Contained in [26] is a very good description of their utility for our problem.

Initial attempts at isolating factors that affect trading yielded mixed results, but when exploring a relatively new domain, negative or inconclusive results may still contain valuable information. A multitude of day trading strategies from ‘resistance and support’ [27] to the ‘market making with volume control’ [10(b)] strategy discuss volume of trades (or the size of the buy or sell trading order in number of shares) as a parameter, in the former case, to aid the decision process and in the latter, as a control mechanism. Most studies however, have considered this a secondary factor and hence, literature on studies of its exclusive effect on intraday trading is scarce. Order imbalance in volume [10(c)] emerged as a useful volume parameter. Initial tests and an attempt at designing a useful day trading strategy yielded useful information, despite some inconclusive results, regarding the merits of order volume as a consideration when designing a trading strategy.

There exists an immense body of work on the mathematical analysis of the behavior of stock prices, stock markets and successful strategies for trading in these

environments. In recent years, the application of artificial intelligence (AI) techniques to technical trading and finance has experienced significant growth. Neural networks [28] have received the most attention in this regard and have shown various degrees of success. The purpose of using neural networks is the ability to forecast data patterns that are too complex for traditional statistical models. However, it is the lack of interpretability of rules generated by a neural network that has caused a shift of interest in favor of more transparent methods, and the genetic algorithm has risen in prominence as an optimization tool in financial applications.

Many traders aim to practice technical analysis as systematically as possible without automation while others use technical analysis as the basis for constructing systems that automatically recommend trade positions. A good example of research where attention is paid to *system construction* as opposed to *rule construction* is [29]. Other work in this area includes [28] who proposed using the method of genetic-based global learning in a trading system. Here, genetic algorithms are used to attempt to find the best combination indicators for prediction and trading. Results are shown to be profitable but are reported in too little detail for objective scrutiny.

In [14], a financial currency exchange system that uses genetic algorithms to optimize parameters for a simple technical trading indicator is described. This work has considerable merit since intraday data are used. It is noted that the ultimate aim of such a project would be to create a system based on an ensemble of indicators as we attempt. A framework for systematic trading system construction and adaptation, based on genetic programs was suggested in [30]. In [1], the use of genetic programming to discover profitable trading rules was explored. A good introduction to genetic algorithms can be found at [31]. Additionally, their use in investment strategies is described in [32].

Work in using a multiple model approach for development of an effective intraday trading strategy [10a] and attempts at designing a strategy in the PLAT domain using reinforcement learning and hill climbing as well as a market maker to be used in

competition in the PLAT domain have been explored to some extent [10b], but not in conjunction with technical trading rules.

2.1.2 Relevant Trading Terminology

Before we discuss the environment and design involved in our work, we will discuss the underlying mechanics of financial markets and exchanges, or the *market microstructure*. In electronic markets such as NASDAQ, all orders are sent to the exchange via an electronic interface and order-routing system. Since orders are cleared electronically, the use of Electronic Crossing Networks (ECNs) has become prevalent. One of the larger ECNs is Island [4].

Electronic Trading uses *orders* to buy or sell shares. These orders may be placed at any price and any number of shares may be traded. Most commonly, we use *market* and *limit* orders. A *market order* is an order to buy or sell shares at the current market price. A *limit order* is an order to buy or sell a security at a specific price. In other words, this kind of order is used to buy shares at a lower price than the current price or sell shares at a higher price than the current. This kind of order does not guarantee a trade, and such an order will be executed only if the current price happens to reach the quoted price.

Most of the strategies described in this thesis use the limit order – and the terms 'order' and 'limit order' are used interchangeably in the following sections.
An *order book* is essentially a sorted list of orders placed by traders. The orders to sell and buy are stored in the *sell* and *buy* order books respectively. Incoming (new) orders are compared with corresponding orders in the opposite book – to check if it can be executed immediately. If it can be executed, the corresponding order in the opposite book is deleted to the extent to which it satisfies the order. If the incoming order is large, then more than one order in the opposite book may be executed to satisfy the need. Incoming orders that are not immediately executed (partly or fully) are entered into the appropriate

order book in an appropriate position ranked by price and time of order placement (in case of a tie).

MSFT

LAST MATCH		TODAY'S ACTIVITY	
Price	24.0700	Orders	52,983
Time	14:57:07.72	Volume	10,243,212

BUY ORDERS		SELL ORDERS	
SHARES	PRICE	SHARES	PRICE
500	24.0620	500	24.0690
6,000	24.0610	500	24.0690
5,000	24.0600	500	24.0700
100	24.0600	200	24.0800
1,100	24.0550	1,981	24.0900
100	24.0500	412	24.0900
5,000	24.0500	3,000	24.0980
200	24.0500	500	24.1000
3,294	24.0500	100	24.1200
1,000	24.0500	2,800	24.1400
3,000	24.0430	5,000	24.1400
100	24.0400	1,000	24.1400
5,503	24.0400	5,000	24.1500
2,100	24.0300	400	24.1600
2,800	24.0300	1,000	24.1700

Figure 2.1: A typical electronic trading order book

Order book *imbalance* is the difference in price or volume of trades between the sell and buy order books. Volume of trades is usually expressed as number of shares associated with orders. Programs written by stock traders/organizations with the specific intent of placing trading orders, according to an algorithm is defined as an *agent* in the following sections. These agents monitor price variation, and based on the programmed algorithm, place orders. Of course, various levels of autonomy can be assigned to the process. Human intervention can be enforced to a high level – wherein the human trader uses the algorithm purely as an indicator or recommendation, and on the other hand, the agent may have more autonomy and is allowed to automatically place bids on behalf of the trader. In this thesis, and all the following sections, we program *strategies* (that monitor current market statistics, and based on the algorithm, decide the action to be taken) that the agent uses to perform certain trading actions.

2.1.3 Stock Market Simulators

Automatic trading has been an active area of research over the last decade, and a primary requirement to this cause is a realistic simulation of the market – owing to the high expenses associated with experimenting on the actual market. This has led to the development of numerous simulators (virtual markets). These simulators have been designed from various perspectives – from the study of market mechanism to classroom teaching of finance fundamentals. The Santa Fe Artificial Stock market project is an example of the former and [20], the latter. The Stock Market Game [33] is a simulator where participants can study the tradeoffs in risks and rewards in making decisions according to certain strategies. Another simulator that can be used by traders to experiment on managing different portfolios is the Virtual Stock Exchange [34]. However most of these simulators create whole new stock exchanges, independent of the real world trades.

The bids placed by the agent needs to affect the economy of the market it trades in. So, in any scenario where *virtual* bids are placed at current prices over a period of time and evaluated in a real world economy, the economy is not affected by any action of the agent. All the above shortcomings in various stock market simulators motivated the research of the Penn-Lehman Automated Trading (PLAT) group. The PLAT simulator seamlessly combines the virtual orders from participating virtual trading agents with orders in a real world ECN, to create an environment very close to the real world. The Penn Exchange Server (PXS), a component of the PLAT project , is a platform for developing novel, principled automated trading strategies. The real-data, real-time nature of PXS lets us examine computationally intensive, high frequency, possibly high-volume trading strategies.

2.1.4 PLAT Domain

The Penn Lehman Automated Trading (PLAT) domain uses the Penn Exchange Server (PXS) to which the trading agents can plug in. PXS uses real-world, real-time

stock market data for simulated automated trading. It frequently queries the Island electronic crossing network's (ECN) web-site to get the most recent stock prices and buy and sell *order books*. A detailed discussion of the working of PXS can be found in [19]. PXS works in a manner very similar to a regular ECN. The order books maintained by the PXS server are a combination of real orders and *virtual* orders (placed by the agents that are plugged into it). *Real* orders correspond to those on the Island ECN. At every processing cycle, an attempt is made to match *virtual* orders. All possible transactions are processed, following which, an attempt is made to match the virtual orders with real orders. After this is over, all remaining unmatched orders (virtual and real) are combined to form a single pair of buy and sell order books. The simulator also computes the profit and losses of each connected trading agent in real time, and displays it in an output file.

PXS is equipped for testing strategies on historical data and also for running in the live mode, starting and ending at the same time with normal trading sessions of the NASDAQ. The simulator supports limit orders only. The trading strategies connected to the server, which we have until now referred to as an *agent* will now be used interchangeably with *client* for the rest of this work. In the simulation, the best ask price is the lowest price any seller (either trading agents or outside market customers) has declared that they are willing to accept; the best bid price is the highest price any buyer has declared that they are willing to pay. If a new buy order has bid price greater than or equal to the best ask price or a new sell order has ask price less than or equal to the best bid price, the order will be matched in the amount of the maximum available shares and the trade is executed. If a bid price is higher than the ask price, the trading price is the average of these two (bid and ask) prices. If orders cannot be matched immediately, they are kept in the queue to wait for possible future matches.

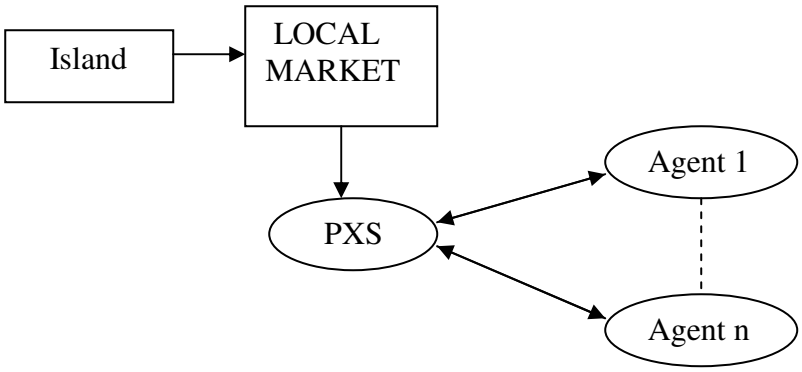


Figure 2.2: PLAT System Architecture

Currently, PXS supports four stocks. However, during the early stages, they were hardwired to Microsoft Stock (Symbol: MSFT). Hence, in this work, our focus is on trading this stock alone. Trading agents in the simulation can buy or sell MSFT stocks with limit orders. Agents can borrow stocks from the simulator and go *short* or borrow money from the simulator without any interest to go *long*. However, the same amount of money will be deducted from the agent's simulated cash account. The cash in the account can be negative or positive. The value that a trading agent has in the simulation can be approximated in real time by the formula: *value* = *cash* + *holdings* * *current Price*.

In the experiments in the rest of this thesis, we impose some rules that are the same as the ones used in recent competitions held by the group responsible for the running of the PLAT domain. We now discuss these rules, which were established external to the working of the PXS server itself. An important feature of the trading simulation is that the objective is to *day trade* (the objective of day trading is purely to trade profitably over a day's stock price variation, and the frequency of observation of price variation as well as order placement is high – many times in a day) and hence, it is strongly desirable to *unwind* one's position, i.e., buy back all the shares from a short position or sell all the shares from a long position by the end of the trading day, leaving the agent at a neutral (zero surplus, zero deficit) position in terms of number of shares. Failure to do so results in a penalty (specific penalty for our experiments are examined in

later sections). Any excess shares held at the end of the day are valued at zero. Shares that are short need to be bought back by the agent at twice the closing price.

Other factors to be accounted for are the fact that trading happens continuously and in real time. The agent strategy cannot be externally changed in the middle of a trading day. Also, PXS has provisions to accommodate transaction costs, much like the real market. Each time a trade is executed by PXS, one side of the order exists in one of the order books already, and the other side of the order is the *incoming* order. In order to reward an agent for providing *liquidity* (providing the books with unfulfilled orders to match potential orders from the other side of the book), the agent that has its order in the book already – is rewarded with a rebate. The agent with the incoming order correspondingly is charged a *fee* – as it eliminates liquidity from the order books. The daily return is thus defined as:

Daily Return = Cash – Unwinding Penalty – Transaction fees + Trading Rebates

The transaction fees charged for trade, in the experiments in this thesis, follows exactly the pricing mechanism of the Island ECN. For each trade executed by PXS, the agent whose order was already in the books receives a REBATE of $0.002, and the agent who placed the incoming order (that was executed immediately) pays a transaction FEE of $0.003. This way, agents are rewarded for maintaining liquidity on the server and penalized for depleting the liquidity. Within the framework defined so far, the objective of the agent strategy is to maximize profits. Specifically, the expected return, measured by the *Sharpe ratio*, is to be maximized (section 2.4). There are competing objectives at play here. The need to maximize profits implies that an extreme position be taken by trading as much as possible when an opportunity for profit is seen. On the other hand, the need to unwind one's position at the end of the day as well as the strict statistical measure of performance suggests a more cautious approach. There are no limits to how many shares an agent may buy or sell in a day, or how many shares an agent may hold (or have a deficit of) at any given point of the day. So there is room for exploration of strategies. Unreasonable positions are avoided by most agents due to the focus on liquidity, but

counter-intuitive, extreme strategies are accommodated within this framework.

A key point to note is that it is desirable to make consistent small profits over many days, as opposed to adopting strategies that provide high returns but result in high variance, thereby neutralizing the profits and resulting in a small Sharpe ratio. The need for a *controlled* trading strategy is evident.

2.2 EARLY AGENT DESIGN AND THE NEED FOR A COMPOSITE STRATEGY

Some financial and commodity market traders study market price history with a view to predicting future price changes in order to enhance trading profitability. This study is called *technical analysis*. Technical trading rules involve the use of technical analysis to design indicators that help a trader determine if current behavior is indicative of a particular trend, as well as the timing of a potential future trade. Owing to the difficulty of managing complex models of the market and using rigorous, adaptive decision techniques, day traders tend to use simpler and more intuitive decision rules. This 'common sense' approach has often proven quite effective [10a] and has been considered a good candidate for automation [35].

The hypothesis is that a robust strategy can be designed by composing multiple 'intuitive' strategies. Robustness and relatively complex behaviors can be achieved by synthesizing multiple, intuitive strategies. Basic stock trading is commonly perceived to be governed by the dictum 'buy low, sell high'. If an agent were to buy a share at a low price and sell it at a higher price, then a profit of *high price – low price* has been made. Numerous such trades over the day would accumulate profit for the trader. A problem in stock markets is that the future is unknown and it is therefore unclear if a decision to buy or sell in anticipation of a favorable movement in the future would yield profit. This decision is further complicated by the strict need to unwind, as is the case in intraday (high frequency) trading. The aim is to leverage the small price changes to one's advantage. A process of *unwinding*, i.e. the process of selling excessive shares if in excess and buying the number of shares required to make up the deficit, when short, is

implemented in the experiments in the following sections. (The case of possible retention of a short or long position overnight, is a different body of research, and includes factors such as overnight information, adjusted prices, etc).

Synthesis of multiple rules to come up with a composite trading strategy has been tried before in various forms – with the component rules being everything from complete rules [36] to very basic predicates and operators that are combined to generate complex rules [37]. In this work, we aim to synthesize a strategy where the component rules are independent strategies in themselves, so they would appeal to a human trader. It would be hard to intuitively see the utility of a rule that was a long series of conjunctions and disjunctions of basic predicates. So, we aim to see if existing, simple, intuitive strategies can be composed in some way to make a robust, profitable strategy. In the following subsections, we will briefly discuss some of the strategies that have been implemented and tested in the PLAT domain, with emphasis on the ones we will use as competitive agents in experiments in later sections.

2.2.1 Static Order Book Imbalance (SOBI) Strategy

The SOBI [10d] strategy bases its decision on the differences in the distribution of volume at different prices in the BUY and SELLS order books.

Let b_i (i = 1, 2, 3, 4) represent the *volume-weighted average price* (VWAP) of the top i*25% of the volume in the buy order book. For instance, b1 is computed by taking the top 25% of the buy order volume, and computing the average price offered per share. Similarly, let si (i=1,2,3,4) be the volume-weighted average price of the top i*25% of the volume in the sell order book. Also, let lastPrice be the most recently updated market price.

Si: si – lastPrice

Bi: lastPrice - bi

Note that Si and Bi will always be positive numbers.

They can be interpreted as a measure of the "distance" from the last price of the top i*25% of the respective order book. The strategy computes the VWAP of the PXS BUY and SELL order books, and compares them to the PXS last price.

The basic idea is that the the difference between the respective VWAPs and the last price is an indicator of the level of support that the buyers and sellers show. For example, if the VWAP of the buy book is much further from the last price than the VWAP of the sell book, it is a sign that buyers are less supportive of this price than are sellers, as indicated by their limit orders (statistically) standing further off. In this case, SOBI will place an order to sell shares, on the theory that the weaker buy-side support will cause the price to fall.

To summarize, the SOBI strategy, at every tick, computes Si and Bi and places buy or sell orders according to the following rules:
If (Si - Bi > theta), place an order to buy volume(v) shares at (price);
If (Bi - Si > theta), place an order to sell volume(v) shares at (price);
theta being a controlled parameter.

2.2.2 Market Maker

A market maker buys stock when the price is increasing at an increasing rate and sells stock when the price is decreasing at an increasing rate. However, rather than wait for a trend reversal to unwind the accumulated share position, the agent always places buy and sell orders in pairs. When the price is increasing at an increasing rate, the agent places a buy order at price p (based on the order book) and immediately places a sell order at price $p + \delta$, with the confidence that the latter will be matched shortly when the price has gone up enough. The situation is assumed to be symmetric when the price is decreasing at an increasing rate. For further discussion, the reader is pointed to [38]. In our tests, this (having been a successful agent in past competitive tests) is used as a competing agent.

2.2.3 Volume Based Strategy

Volume of trades and order book volume imbalances have long been established as important criteria in evaluating portfolios [39] and long term investment strategies. The hypothesis [10c] is that it is an essential component of intraday trading strategies – important enough to be effectively used exclusively as an indicator of the market behavior. We conjectured that price based measures need to be coupled with *order imbalance in volume* (the difference in total volume of shares on either side of the order books) to make it more sensitive to the 'confidence' of the investors in the midst of a trend. Unlike the SOBI strategy (section 2.2.1), where the volume weighted *price* difference between either side of the order book is used to base a trading decision, we conjectured that such a decision can be made using the *volume* of orders alone (on either side of the order book).

Another hypothesis on volume effects was that very high volume of trade in the market coupled by a period of unidirectional price increase/decrease indicates continued unidirectional trade. An explanation for such behavior could be the occurrence of product releases, earnings announcements, bullish and bearish announcements or other *private* information that an agent might use to trade one way or another. This should be an overriding factor in the agent decision process, and thus prevent the agent from going very long or very short without any hope for recovery. If large volumes of trade are coupled with unidirectional movement in price, this may be an indication of the possibility of extreme long or short trading.

The basic strategy was implemented as follows. The order book data was obtained for each update (in time, say t1) and the corresponding volume of unmatched shares on the buy and sell sides of the book. The difference of these volumes is the buy-sell difference. Then, this same difference is obtained for the next time update (say time t2).

The decision rule is stated as:

If $(buy - sell)_{t2} > (buy - sell)_{t1}$

buyOrder(buyprice, ordervolume);

Else If $(buy - sell)_{t1} > (buy - sell)_{t2}$

sellOrder(sellprice, ordervolume);

Else do nothing

The volume of orders was tuned with an optimization algorithm that maximized the function:

$$\sum[\{(sellprice * ordervolume) - (buyprice * ordervolume)\}(t)] - [2 * price * |\sum vol1 - \sum vol2|]$$

where *vol1* and *vol2* are the buy and sell volumes respectively.

As discussed earlier, in the event that high trading volumes accompanied unidirectional price movement, a cautionary approach was taken and implemented as:

check totalvolume

if (totalvolume is very high)

for (3 time steps)

if (price increases for three time steps)

buyvolume = sellvolume = 0 ;

else if (price decreases for three time steps)

buyvolume = sellvolume = 0 ;

Else do basic strategy

Although crude, this *guard* mechanism proved quite useful.All of these early attempts at designing strategies seemed to indicate the need for combining many simple intuitive strategies, as well as using a more efficient control mechanism to take care of cash and share position.

2.2.4 Multiple Model Strategy

This approach was developed and implemented by Ramamoorthy [10(a)] as part of a project for a class and was a successful agent in competitive simulations in April 2004 (Appendix 3). The intuition behind this strategy is that there are periods of time when the behavior of the stock return is, in fact, mean reverting and a simple strategy

with this assumption would, in a statistical sense, produce profits. When the markets deviate from this favorable model, the resulting effect would be observed from instantaneous cash and stock holdings. This could be used to trigger a mode switch to a different strategy that does not assume the mean-reverting nature of stock prices. In the case of the agents we aim to implement in our thesis, we incorporate this strategy (as is, with a few very minor modifications) in conjunction with our algorithms, as a *control* measure. Intuitively, we can think of this as a faucet that we turn to control various rated of flow. If we think of the trading suggestion and suggested trading volume as the suggested trading parameters, then it is regulated by the action *mode* (safe or regular) suggested by the multiple model mechanism, which we describe [from 10(a)] below.

The problem of detecting the agent and the market's mode can be approached by thinking in terms of two key variables – cash held by the agent and net shares held by the agent. This representation can be visualized as a two dimensional state space, the axes being cash axis and share axis respectively. The idea is to move in the positive direction on the Cash axis while trying to stay close to zero on the Share axis. The effect of the market is to move the agent's current position along the Cash axis towards the negative side. The agent, on its part, can issue commands to move along the Share axis. Occasionally, the agent's state is far from the Share axis.

So, the idea is to explicitly control risk and rewards by tuning the one variable available to the agent, the share holdings, in response to observed variables, the last price. The allowed modes of trading the agent can follow are:

Regular: Perform trading as usual.

Safe: Try to divest holdings when profitable, otherwise, do nothing. This would never increase holdings in the unfavorable direction (in the state space).

Risk Seeking: Trade with lower margins and larger volumes in expectation of higher returns.

These behaviors can be composed as shown in the table below:

Cash Share	Very Negative	Negative	Zero	Positive	Very Positive
Very Short	Safe	Safe	Safe	Safe	Safe
Short	Safe	Safe	Regular	Regular	Safe
Zero	Safe	Regular	Regular	Regular	Risk Seeking
Long	Safe	Regular	Regular	Risk Seeking	Risk Seeking
Very Long	Safe	Safe	Safe	Safe	Safe

Table 2.1: Mapping position in cash-share space to a mode of action

2.2.5 Other Strategies

Numerous other strategies have been implemented in the PLAT domain and implemented in competitive runs, with varying degrees of success. Among the more successful of these agent strategies, is the Reverse Strategy [48]. This strategy runs counter to the traditional dictum of "sell when the price is falling and buy when it is rising". It buys when the price is dropping and sells when the price is rising. Other techniques explored use trader message boards and gleaning information from the news online [51]. In the following sections in this chapter, we briefly discuss evolutionary algorithms and trading evaluation criteria with relevance to the central strategy discussed in this thesis.

2.3 GENETIC ALGORITHMS AND GENETIC PROGRAMMING

The areas of artificial intelligence and its application to technical trading and finance have seen a significant growth in interest over the past few years. Specifically, the use of evolutionary methods such as *genetic algorithms* (GA) and *genetic programming* (GP) in this domain has been examined. These approaches have found financial applications in options pricing [40] and as an optimization tool in technical trading applications [30].

Evolutionary learning algorithms derive inspiration from Darwinian evolution. GAs are population-based optimization algorithms and the first proposal of this idea has been credited to Holland [41]. They have since found applications in a wide range of problems. GPs are an extension of this idea proposed by Koza [42] with a view to evolving computer programs.

GAs are iterative systems and aim to find near optimal solutions. They differ from standard search algorithms in that they use a population of possible solutions rather than tuning a single one. Although convergence to the global optimum is not guaranteed, they are quite robust in producing near optimal solutions to a wide range of problems and, in particular, those that are not easily reducible to a precise mathematical formulation. In pseudo code below, a basic genetic algorithm (a formulation we stick to reasonably accurately) is described.

PSEUDOCODE (adapted from [54]):

```
Begin GA
  g:=0                          { generation counter }
  Initialize population P(g)
  Evaluate population P(g)  {i.e., compute fitness values}
    while not done do
          g:=g+1
          Select P(g) from P(g-1)
          Crossover P(g)
          Mutate P(g)
          Evaluate P(g)
    end while
End GA
```

The starting point in using GAs to solve a problem is to represent the problem in a way that a GA can work with. This often amounts to representing the solution space as a finite number of strings of binary digits. *Binary strings* are an effective form of representation since complex statements as well as numerical values of parameters can be represented in this form. The resulting search space is finite when parameters take only discrete values to yield a binary representation as a string of fixed length. Secondly, there needs to be a means of evaluating the *fitness* of the constituents of the solution space, i.e. the suitability

of each potential solution, for how well they perform. For example, in the case of selecting trading rules the fitness could be viewed as the profitability of the rule tested over a time series of historical price data, or a function of this variable.

Genetic Programs are a variation of the standard genetic algorithm, wherein string lengths may vary within the solution space. Unlike in GAs, solutions in GP can be seen as non-recombining decision trees [43] with non-terminal nodes as functions and the root as the function output. These are usually the optimization algorithm of choice in cases of evolving strategies based on Boolean operators – when the solution may be evolved with varying depth in the tree [44]. It is inherently more flexible than the GA, but care needs to be taken in representation to avoid *over-fitting* (the phenomenon where a classifier is trained too minutely to fit the training data – causing diminished performance on data outside of the training sample, also called out-of-sample data).

2.4 PERFORMANCE CRITERIA

A class of performance criteria commonly used in the financial community are measures of risk-adjusted investment returns. Risk-adjusted returns are a measure of the returns of an asset adjusted for risk or volatility. In other words, consistency is rewarded and volatile trading patterns are not. Common measures within this class are the *Sharpe* and *Modified Sortino* ratios.

2.4.1 Sharpe Ratio

Probably the most popular measure of performance of asset trading in finance is the *Sharpe* ratio, introduced by William Sharpe [45], and originally introduced to measure the performance of mutual funds. Essentially, it is excess return divided by risk as measured by the standard deviation of return. For the rest of the thesis, we will assume that 'return' is 'daily return'. We recall from section 2.1.4 that daily return, for our experiments, is defined as:

Daily Return = Cash – Unwinding Penalty – Transaction fees + Trading Rebates

If the average daily return (defined as the amount of money made after money spent and sale of remaining stocks are adjusted for, at the end of the trading day) is supposed to be R_i then the average daily return is:

$$\overline{R} = \frac{1}{N}\sum_{i=1}^{N} R_i$$

The standard deviation of returns is,

$$\sigma = \left(\frac{1}{N-1}\sum_{i=1}^{N} \left(R_i - \overline{R}\right)^2 \right)^{1/2}$$

Thus, the Sharpe ratio is,

$$Sharpe\ ratio = \frac{\overline{R}}{\sigma}$$

2.4.2 Modified Sortino Ratio

Despite the common use of Sharpe ratio in the field of financial performance evaluation, quite often, traders are often not perturbed by the possibility of volatile return structure provided the strategy is mostly profitable. Sortino ratio, introduced in the early 1980's, is a modification of the Sharpe ratio that differentiates 'harmful volatility' from volatility in general, using a value for downside deviation only. While it has limited basis in theoretical study in the area [46], we hypothesize that it warrants a closer look, especially in the domain of intraday trading agent performance evaluation.

The Sortino ratio, as defined in [46], is a more complex model - suitable for rigorous statistical evaluation of asset returns – than we aim to use in the experiments of our thesis. A usable form of this ratio, which we will use in following sections, is:

$$Modified\ Sortino\ Ratio = \frac{\overline{R}}{\sigma_{neg}}$$

where σ_{neg} is the standard deviation of negative returns only (over the given period of time). $\overline{R}$ represents the returns (as described in section 2.4.1).

2.5 THE DATA

The PLAT domain is an experimental test bed that is configured to run with the historical as well as live mode data. The data comes from a mirror of the Island ECN which trades NASDAQ stock. The only stock used here is the Microsoft (Symbol: MSFT) stock. The stock data consists of a *bid* and an *ask* price table, that lists in order of preference, the respective orders placed by agents/traders. The difference between the topmost entries of this table is called the *spread*. A number of past trading days' books are stored in the PLAT project. The process of selection of data (trading days) used for training and testing is as follows. There were days from early December 2003 to mid July (archived in the PLAT project for MSFT) that we used as a baseline set of data for consideration for our thesis. Over half of these days were eliminated due to incomplete data over the day or corruption of data. Of the remaining days, attempts were made to make sure the data included data representative of a number of different stock behaviors over a training day. Specifically, we made a list of all the days in the archives, which we deemed as tradable after weeding out incomplete data, and this list was checked with a list of trading data we obtained from Yahoo! Finance pages [52]. The data, based on details such as opening price, closing price, high and low prices of the day, was divided into various categories such as *increasing, decreasing, mean reverting*, etc. Further discussion on the classification of days based on price dynamics is included in Appendices 1 and 2. Our final list included 60 days. Of these, 15 days were set aside for our competitive tests with previously successful agents. The remaining days were split up into training and test days, and we made sure that no experiment had any overlap between its training and test set of days.

Chapter 3. Agent Design

In this chapter, we will discuss design issues, and the techniques used in development of agents for trading in PLAT domain. Our primary aim is to design trading strategies that resemble a technical trader who would systematically, and based on a set of pre-specified evaluation criteria; choose a subset of trading strategies from a larger set of trading rules, and evaluate the performance of these strategies in various competitive scenarios. The basic idea is to combine popular, 'intuitive' technical analysis indicators and rules to profitably trade in the PLAT domain. Trading strategies and rules are allowed to combine in two different mechanisms – with the use of genetic algorithms and genetic programs – to evolve strategies that are aimed to be profitable, and perform well, under the different evaluation criteria involved.

3.1 GENETIC ALGORITHM AGENT (GAA)

In an attempt to make a profitable, robust strategy using simple intuitive laws that appeal to the human trader, we use multiple technical trading rules in a weighted combination to produce a unified strategy. In addition to designing an automated strategy that is intuitively appealing, the generation of effective strategies using complete, comprehensible indicator strategies may help in the understanding of these component strategies, their effects and limitations.

In this formulation, we use a number of basic (indicator) strategies in a weighted combination to produce a cumulative trading action at every tick (a *tick* in the following sections is the point in a trading day when the books are updated and fresh data is available). The algorithm uses principles from the weighted majority algorithm [47] in the use of *suggestions* from the component strategies and combining them using a weighted majority. We propose the use of a similar suggestion or voting mechanism wherein each indicator would signal a *buy, sell* or *do nothing* action. We recall that the steps involved in trading in this environment include getting the raw order book data, evaluation of a recommended action by each of the indicator strategies and combining these indicators using the respective weights giving us a cumulative suggestion (a

weighted majority). This is followed by a multiple model control mechanism that determines the *mode* it should trade in (A discussion of *modes* of trading is in section 2.2.4). Earlier, we compared the control mechanism to a faucet, acting as the final regulator on the trading decision and volume suggested by the composite strategy so far. It has the power to veto a trading decision suggested by the composite algorithms, when in the *safe* mode or allow the trade to continue unaltered in the *regular* mode.

The multiple model control mechanism determines the trading *mode* based on current holdings of the agent (also called the share position). The *share position* is the number of shares that the agent has accumulated (long position), or the number of shares that is deficient (short position), over the trading day up to that point. It is not difficult to imagine that a human trader would behave differently when in an extremely long or short position (risk averse) as opposed to when he is in a relatively neutral share position (risk neutral or risk seeking). A similar behavior is desired from an autonomous automated agent in determining the trading action to be taken. The agent evaluates its current share position and this helps keep the agent from following a possibly unidirectional market trend to the end of the day, and reaching a very long or short position. In essence, this mechanism is a control measure to ensure the agent achieves a share position as close to neutral (zero accumulation or deficit) as possible. In section 2.1.4, we discussed that *unwinding* is an important constraint and enforced external to the mechanism of PXS. With the use of Sharpe and Sortino ratios, the imposition of this rule makes sense in that it provides for a uniform set of statistics to evaluate trading agents on. We achieve the objective of unwinding with the use of a multiple model mechanism. One of the changes in our implementation, when compared to that in section 2.2.4, is that we have eliminated the use of the 'risk-seeking' mode of operation. The reasoning behind this decision is that such a behavior is proposed only for extremely high cash as well as share positions. This is not only a highly unlikely occurrence, but also a situation where we hypothesize a *regular* behavior should suffice in recovering a reasonable share position – keeping in mind the relatively robust design of the market evaluation phase of the strategy. This multiple model scheme examines the agent's share position and provides a *mode* of

operation that the agent should follow. This regulation is combined with the decision that is output by the composite strategy and we arrive at a final trading decision to *buy, sell* or *do nothing*, and the volume to be traded. In the figure, the four *indicators* (MAS, VS, PS and PCBS) are the result of each component technical trading rule and their suggestion based on the market information they receive. We will discuss these indicators in greater detail at a later time. An important point to note at this time is that the indicators, although complete strategies in themselves, provide us with nothing more than suggestions to buy or sell. The reason for ignoring the volume of trade that may be possible to obtain from each indicator is that this would require us to optimize the volume parameter for each of the indicators, and then applied tuned weights to them. This adds to the burden of computation, and is avoided in this thesis. We do not use these indicator strategies to give us specifics such as the volume or price at which to place trading orders. Weights ($W_{1...}$ $W_{4)}$ are applied to the indicators to arrive at a weighted suggestion W*I. The final decision depends on this weighted suggestion as well as the output of multiple model control mechanism to give us the *final action* to be performed by the agent. The weighted suggestion to trade a certain way determines the *volume* of shares to be traded at that tick.

The order placement is done online based on the information obtained from the updated order books and current agent statistics (both of which are obtained from the PXS and client statistics respectively). The weights ($W_{1...}$ W_4) are tuned offline using a genetic algorithm (GA). The weights are each represented as 2 discrete bits in a bit string. Also included is a sign bit associated with each weight. The sign bit is used to evaluate the effect of the weight on the rule. For example, if an indicator suggested a *buy* action, and if the weight W_n had a negative sign, then the weighted suggestion would be to *sell*. This representation is particularly useful in the expansion of search space available to the GA as well as in compensating for some representations of the component (indicator) strategies that may in fact be useful as a parameter to be observed, but the decision rule may be quite the opposite of our assumption. A good example of such an occurence is the use of ‘direct’ and ‘reverse’ strategies in [48]. In it, an initial attempt at using a simple

decision rule based on current and previous price used a *buy* action when the price increased and *sell* action when the price deceased. However, when they switched the actions to use a *sell* action for increasing price and a *buy* action for an increasing price, it yielded superior performance. Such occurrences would be compensated for with the use of the sign bit in our bit string as the GA is expected to tune itself for better performance.

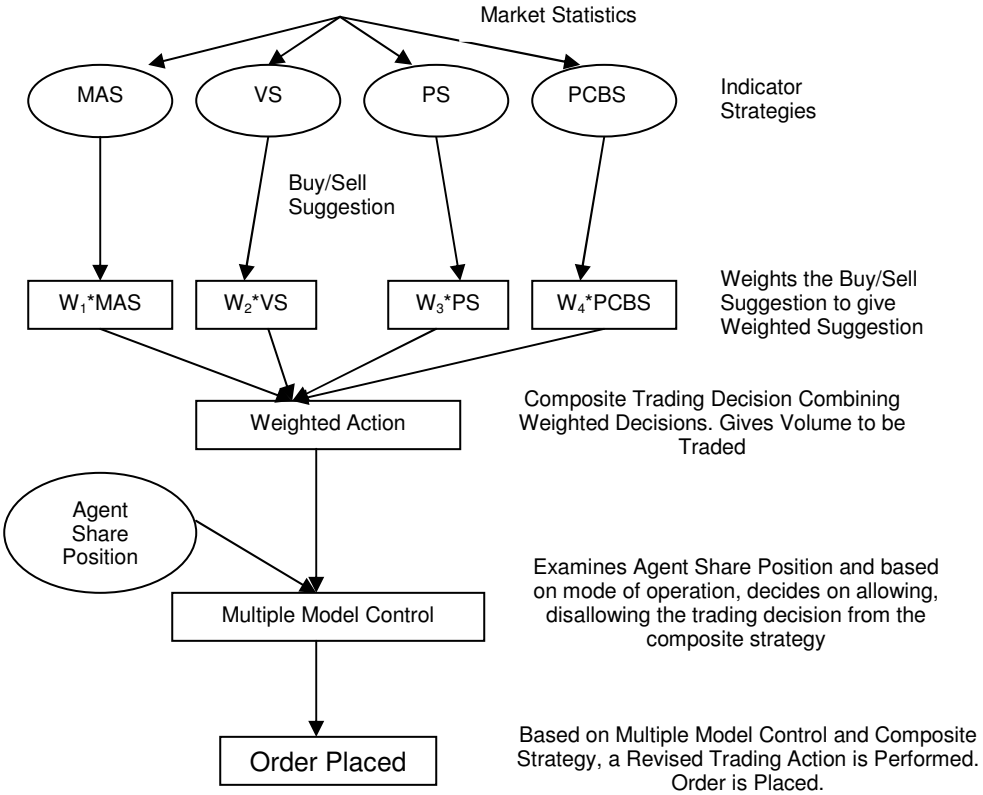


Figure 3.1: Overview of working of the GA agent

From Figure 3.2(a), we can see that the 2 bits corresponding to each weight can take on 3 discrete non-zero values for each of the positive and negative signs prefixing them. In all, there are 7 possible values for each weight. In Figure 3.2(b), we've described the structure of bit strings for buy and sell strings. Figure 3.2(c) describes how the weights combine to affect the *volume* of trade. The weights (along with the sign) can combine to give us a value of combined strength that ranges from -12 to +12. This combined strength

value is then multiplied with a constant volume factor (the value of this was fixed empirically at 25 throughout this thesis) to give us the volume of shares to be traded at that particular tick.

Bit Pattern	Strength of Suggestion
00	0 (No trade)
01	1 (Weak)
10	2 (Strong)
11	3 (Very Strong)

Figure 3.2 (a) Correspondence of bit patterns of weights to strength of suggestion

BUY	SIGN	W1	SIGN	W2	SIGN	W3	SIGN	W4
	0	01	1	11	0	00	0	10

SELL	SIGN	W1	SIGN	W2	SIGN	W3	SIGN	W4
	0	00	1	10	0	01	0	01

Figure 3.2 (b) Structure of the buy and sell bit strings that populate the GA

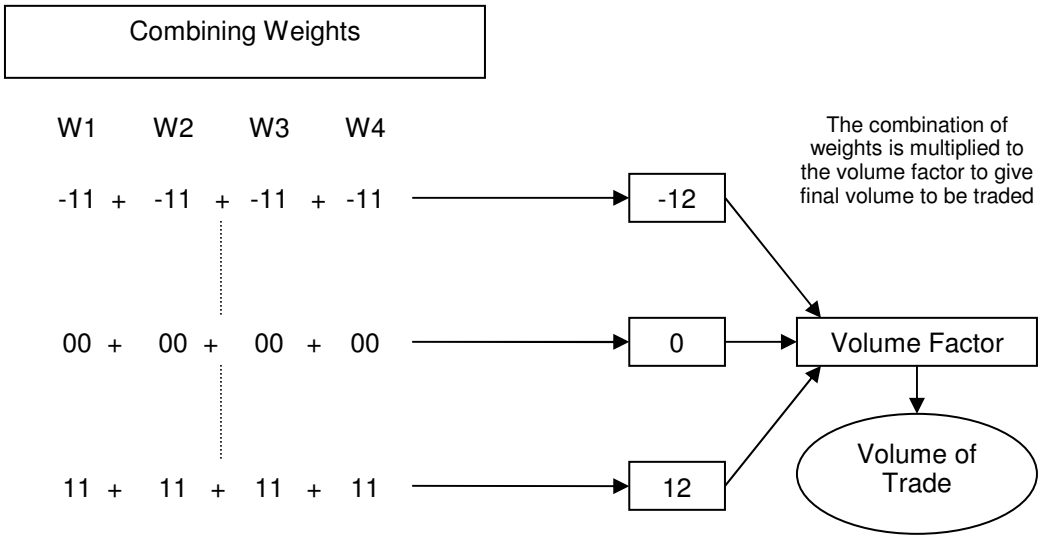


Figure 3.2 (c) Combining weights and volume factor to get volume of trade

The length of the bit strings are limited to 12 bits (2 bits and a sign bit for each indicator), due to the burden of computation time. The reasoning was that longer strings would make the search space of possible solutions much larger (owing to the increased number of unique combination of bits. The computation time of the GA, in its current format, already runs into more than a day, as each generation is essentially a simulation over a trading set (15 days run in historical mode) with multiple agents (in this case 20 per generation). The time taken to run the simulation also increases with the number of agents plugged in simultaneously. It is evident that an increase in the number of individual bit strings per generation would be required to search a reasonable portion of the search space, in case the number of bits per string was increased. This would consequently lead to increase in computation time, and training would become a very computationally intensive task. To avoid this predicament, we limited the bit strings to 12 bits, at the cost of increased granularity in weight values.

In preliminary work done in a class, we hypothesized that technical trading indicators are sometimes not symmetrical. The market, as an aggregate, swings upward or downward from an opposite trend – and these effects, when viewed on a chart, are called shoulders. These shoulders may be wider when a downward trend ends and narrower when an upward trend ends, or vice versa, depending on the setup of the decision rule [49]. To incorporate this hypothesis in our design, the trading rules and weights are split into *buy* and *sell* components. Each indicator strategy consists of a *buy* and *sell* recommendation (suggestion) that is triggered by the ME phase. However, buy rules are not necessarily the complementary to the sell rules in manner or strength. Hence, to allow for these variations, we use separate buy and sell rules (Figure 3.2). This reasoning for this modification is as follows. For example, order imbalance in volume on the buy side may indicate strongly that buying stock is the right thing to do, but when the imbalance is on the sell side, the sell signal may not be quite as strong. In many cases, due to numerous factors, symmetrical trends on the buy and sell sides do not imply complementary actions at all times, especially if the volume of trade is considered.

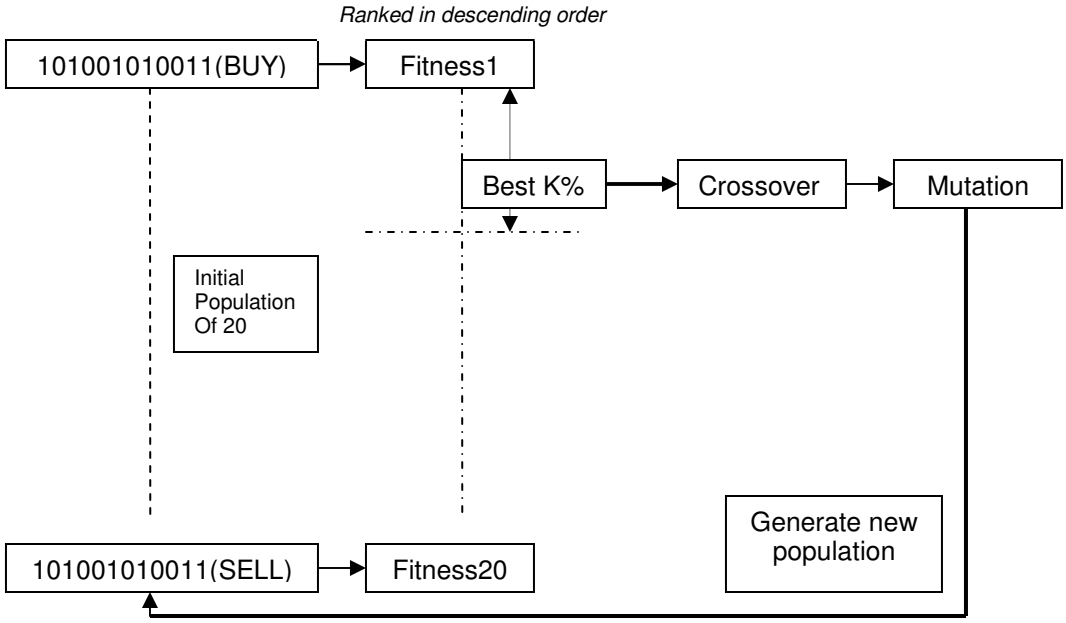


Figure 3.3: The GA for one generation of execution

The final action to be taken is determined as:

$$Action = (W_1 * I_1) + (W_2 * I_2) + (W_3 * I_3) + (W_4 * I_4)$$

where $W_n = (00,01,10,11)$ and $I_n = (-1,0,1)$, with -1 indicating a *sell* action, 1 indicating *buy* action and 0 indicates a *do nothing* action. In the following sections, we will look at details of implementation of the GA and briefly discuss the component strategies (*indicators*).

3.1.1 Genetic Algorithm Implementation Issues

The genetic algorithm goes through the generation of population, fitness calculation, crossover and mutation stages until convergence is achieved or the maximum allowed number of iterations has occurred.

Population Initialization: In the very first generation (beginning of run), the population is initialized using uniform pseudorandom integers which are translated to the strings that

constitute the initial population. We use a population of ten strings for each of the buy and sell rules as the population for each generation. As can be seen in figure above, we have 20 strings that populate every generation. Many factors go into choosing the size of the population in a GA. Sufficient exploration of the search space necessitates a reasonable size for the population. However, here, a mitigating factor was computation time. Our training method included running the population over entire training periods (15 days per training set), and a generation involved running 20 individuals simultaneously on PXS over this entire period. This process took many hours (with 15 training days). For this reason, we found it necessary to keep the number of members in the population down to a manageable number. However, we did introduce a few steps like elitism (the selection of only the top ranking strings in terms of fitness) to encourage convergence. Each subsequent generation is populated as a result of crossover and mutation operations.

Fitness Calculation: The *Sharpe* and *Sortino ratios* (section 2.4) are used as the fitness function to evaluate the performance of each member of a population in every generation. The fitness was calculated as the Sharpe or Sortino ratio of the string over a period of time (15 days if training sets in Appendix 2 are used). The training set of trading days remained the same for each subsequent generation. Hence, the goal of the evolution process is to maximize the fitness functions (and find the combination of weights that does this) for a given set of training days. However, it is possible to find the right set of weights to maximize the fitness over any given set of trading days (given sufficient time and exploration), and we must keep in mind that the ultimate aim is to find the right weights that will maximize profit over *out-of-sample* data (test data different from training data). The strings of weights, after evaluation, are ranked in decreasing order of fitness.

Crossover: Crossover is the process of cutting strategy string pairs at appropriate points and exchanging tails between heads to make a new pair. Only the best *k%* of strategies is

used for crossover, and bit strings are crossed over tail to head. The probability of being selected for crossover is higher for strategies with higher fitness.

The selection of a string ranked *i* is calculated by the formula:

$$p_i = \left\{ \begin{array}{l} \dfrac{k.N - i}{\sum_{1}^{k.N} i}; i \geq k.N \\ 0; otherwise \end{array} \right\}$$

where *k* is the percentage of population to be considered. *N* is the population size and *i* is the rank of the string in the population. Based on this probability, pairs of strings are independently selected (with replacement) from the population and crossed over [in a manner as described in 21]. Once a pair has been selected, a cut point for both strings is uniformly pseudo-randomly selected, so that both strings are cut into two pieces with the 'head' and 'tail' parts of both strings being the same length. Then these tails are crossed over. The resulting strings are next analyzed to check uniqueness relative to the current population by comparing each string bit by bit.

Mutation: Mutation is the process of randomly changing appropriate bits in a strategy string and is executed in a bitwise manner. We maintain an elitist model since the top 2 strings (from each of the buy and sell sides) are spared mutation. This is done in order to preserve strings with high fitness since in this kind of optimization we are searching for maxima locally as well as globally, i.e. we attempt to generate an array of *good* solutions rather than just the best. The generation of such a *set* of solutions rather than a single good solution is done in an attempt to maintain a set of good solutions to search from (and increase exploration). After each attempted mutation, the string is checked bit by bit with the other solutions for uniqueness. In the event that duplicate strings are found, only one of them is retained, and we dip into the remaining (unique) solutions and select the one with the highest of the remaining fitness functions. Also, a brute force implementation ensured that each generation had at least two sell and two buy rules

generated, to ensure that there was never a case when all rules were of sell or buy type exclusively.

We use a relatively high mutation rate, to compensate for the small population size, and to ensure more exploration of the search space. If the population of strings contains B bits, numbered 1 to B, then we would wish to mutate $M = 0.1B$ of them. In this case, M uniform pseudo-random integers are generated between 1 and B without replacement. The M integers are ordered by magnitude and for each the correspondingly numbered bit is mutated (0 goes to 1, 1 goes to 0). After each string has been passed by the mutation process, a bit-by-bit check is performed to test for uniqueness, and duplicate strings are eliminated in favor of unique ones. Elitism also ensures that an arbitrary stopping of the algorithm after a few generations produces a good result.

A lower bound on number of generations is used so even if it converges to a maximum before that, it goes on until a set number of generations are done. Also, an upper limit of generations was used to ensure that it doesn't go on to the point where it takes too much time (as we stressed earlier, the process already takes over a whole day of runtime). *Convergence* is said to occur when mean fitness of a user defined percentage of the most fit strategies and maximum fitness both change by no more than 1% between the previous and current generation.

Figure 3.4(a) shows the convergence of the fitness over generations, for a training run (with training set T_1), and the respective weight values allotted in each generation. In our thesis, we used a minimum number of generations as 8 (to ensure that local minima are avoided) and a maximum number of 10 generations. This proved to be a very small range, and owing to the fact that the GA almost always converged in 8 generations (in the case of our tests), we might as well have done away with the *range* and stuck to a fixed number of (eight) generations. Figure 3.4(b) shows the corresponding weights at each generation for the one test run that we documented. It may be argued that the convergence seems to have occurred in a fairly low number of generations only because

the resolution of weights is so low. This is true, but as we had explained earlier, we decided to sacrifice resolution for the sake of manageable computation times for the training process.

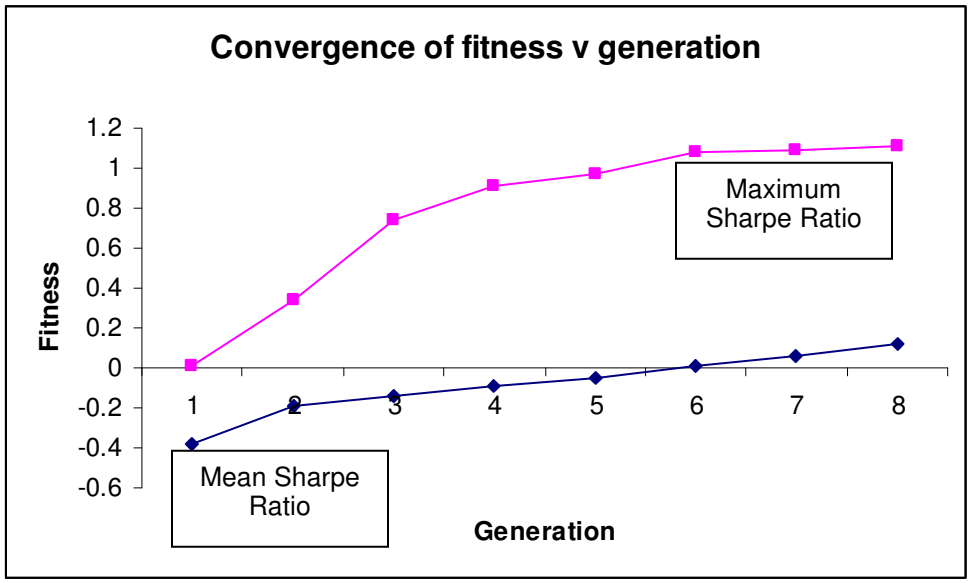


Figure 3.4: Convergence of fitness by generation

Generation	W1	W2	W3	W4	Mean Sharpe Ratio	Maximum Sharpe Ratio
1	01	10	10	11	-0.38	0.012
2	10	10	10	10	-0.19	0.34
3	10	10	00	10	-0.141	0.742
4	11	10	00	10	-0.0897	0.911
5	11	10	01	01	-0.054	0.968
6	11	10	00	01	0.006	1.077
7	11	10	00	01	0.06	1.091
8	11	10	00	01	0.12	1.112

Table 3.1: Weights allotted to the indicators for the individual with best fitness in each of the generations for a particular training run

3.1.2 Component Strategies or Indicators

So far, we have discussed how indicators are combined to produce a weighted suggestion, and how this is used to arrive at a suitable trading action. We now look at the component strategies that are used as indicators in the formulation discussed in earlier sections. Although the strategies below are complete and give, as output, desired trading action as well as the price and volume of the trading order to be placed, we implement them as indicators alone. Thus, we only utilize the trading order suggestion from the component technical trading strategies, and combine them using our weighted majority algorithm to obtain trading volume.

At this point, we aim to clarify some implementation details, helping simplify possible reconstruction of the experiments. Previously, we had assumed that once the action was determined, it would be performed instantaneously. However, this is not always the case. When a buy or sell order is placed, it is not necessary it will be filled. In the event, a decision on the action to be performed was determined using the last price. However, the actual execution involved looking at the order books and the existing entries, and placing an order that is incrementally better than the best offer. The orders placed were \$0.0001 worse than the existing value. This value is small enough not to make a substantial difference in price, yet helping the agent avoid much of the penalty for removing liquidity in the order books by placing itself just behind the top order. In pseudo code, this would be reflected as:

SellPrice = price of top sell order + 0.0001

BuyPrice = price of top buy order – 0.0001

We decided not to optimize the individual parameters (as suggested in section 3.1.1) in an effort to avoid over-fitting the agent to the training data. So, the parameter choices, if any, were determined empirically, over 15 sample days in the training set of days. In each of our component strategies, we defined the order price to be the same and as described above. We used a constant *volume factor* of 25 throughout the thesis. This volume factor is the constant number of shares to be multiplied to the *strength* of the composite

strategy's suggestion. For example, if the four weights all added up to 5 for the buy rule, then we would trade 5*25 = 125 shares at every point when a *buy* order is to be placed.

MOVING AVERAGES STRATEGY

The first strategy used was using the moving average crossover strategy. The moving average of stock prices over a shorter and longer horizon respectively, is taken. The simple moving average is taken as:

$$Moving\ Average = \frac{1}{n}\sum_{i=0}^{n} lastprice_i$$

Here, $n = N_1$ is a shorter horizon window and $n = N_2$ is a longer horizon window such that $N_2 > N_1$. Let moving average over N_1 be MA_1 and that over N_2 is MA_2.

The algorithm:

If ($MA_1 > MA_2$ + Threshold)

Then Sell m shares @ sellprice

Else If ($MA_2 > MA_1$ + Threshold)

Then Buy m shares @ buyprice

Else Do Nothing

A key aspect of this algorithm is that this strategy (depending on the parameters) is capable of making large gains, but is equally capable of making large losses. This can be attributed to a naïve dependence of the strategy on the mean reverting nature of intraday price variation of stock. The decision rule is intuitively simple but has the common problems. If the volume of each trade is too high, the extreme position is all too common and unwinding may be difficult. If the volume is too low, then we are not efficiently utilizing the potential for profit. Variation in the threshold is susceptible to the same problems. A potential solution is to employ volume tuning using an optimization algorithm similar to that in section. However, optimizing both these factors simultaneously, involves finding an appropriate model and that is quite difficult. Throughout this thesis, we used a constant value of threshold on the difference between

two moving averages. The threshold was determined empirically. Setting it too low would make the strategy too sensitive, and the true trend would probably not be captured. Setting it too high would make it sluggish and unresponsive to anything but major swings. We found that a value close to 0.01 proved to give good results. Also, window sizes of 5 and 50 proved to yield good results.

VOLUME BASED STRATEGY

The strategy here remains the same as described in section 2.2.3. The basic strategy involves obtaining the order book data for each update (in time, say t1) and getting the corresponding volume of unmatched shares on the buy and sell sides of the book. The difference of these volumes is the buy-sell difference. Then, this same difference is obtained for the next time update (say time t2). The decision rule is stated as:

If $(buy - sell)_{t2} > (buy - sell)_{t1} + Threshold$

buyOrder(buyprice, ordervolume);

Else If $(buy - sell)_{t1} > (buy - sell)_{t2} + Threshold$

sellOrder(sellprice, ordervolume);

Else do nothing

In the *volume* based indicator strategy, a β factor of 0.1 proved to give us good performance, where β was the multiplication factor in the volume threshold, *Threshold* = β**(average of volumes in two order books).*

SIMPLE PRICE BASED STRATEGY

This strategy is intuitively the simplest to understand. At any time during the simulation, if the stock price goes up, it places a buy order; and if the stock price goes down, it places a sell order. The motivation is that a price rise indicates likely further price rises. It is written as:

If currentprice > lastprice

Buy @ buyprice (ordervolume)

Else if lastprice > currentprice

Sell @ sellprice (ordervolume)

Else Do Nothing

The strategy described here is the same as the one described in [5], where its performance is compared to the 'reverse' strategy. The reason for choosing the direct strategy in the face of results that prove otherwise is to allow for the GA to tune the weights and sign to choose the (presumably superior) 'reverse' strategy if necessary. Essentially, the model we propose includes a sign for the buy or sell order signaled by the component strategies, allowing for use of the strategy in either form.

PRICE CHANNEL BREAKOUT STRATEGY

This strategy involves defining *Bollinger bands* [53], which enclose a price range within the maximum and minimum price of the last few time steps. The *trading range* is defined by the *upper* and *lower* bounds obtained by finding the maximum and minimum prices over the last few time steps.

UpperPriceBandLimit = max(price over last n steps)

LowerPriceBandLimit = min(price over last n steps)

If CurrentPrice > UpperPriceBandLimit

Buy @ buyprice (ordervolume)

If CurrentPrice < LowerPriceBandLimit

Sell @ sellprice (ordervolume)

Else Do Nothing

When the price crosses the upper limit from below, it indicates a *breakthrough* and signals a *buy* action. When the price crosses the lower limit from above, it signals a *sell* action. This is a simple strategy to grasp intuitively. It is easy to imagine that this strategy is useful more as support scheme to bolster a trading signal or to promote cautiousness in trade. The above four indicators are abbreviated as MAS, VS, PS and PCBS respectively,

and will be referred to by these acronyms when the results of our experiments are discussed (Chapter 4).

3.1.3 Training

A number of days needed to be selected for running the genetic algorithm and evaluating the fitness of each member of the population for a generation. A primary motivation for this large baseline pool of days to select days from – is that there tend to be local consistency in the patterns that the days took. There may be days together when the price ended lower or higher than it began, for example. Also, if the pool of selected days consisted predominantly of a particular price dynamic (Appendices 1 and 2), then the algorithm might assign weights that suit that day more than the others, as this would prove to give very good fitness over the training period. However, the true test of performance is over a test set of days different from the training sample. In order to avoid fitting the weights too finely to a certain price dynamic, we aimed to include not only the different major price dynamics (Appendix 1), but also include about the same number of days of each type. This handpicked set of days (*training sample*) will be referred to as training set, training sample or training days; in the following sections. For training, numerous days from December 2003 to March 2004 were used (from the PLAT historical books). After a weeding of a number of the days due to incomplete information or corrupted files, 60 of the archived dates were split up fairly evenly into test and training sets of days. In all the experiments in this thesis, the training and test sets for the given test consist of different days, i.e. an intersection of their sets would be empty. A hybrid of training days was used with some days being 'representative' (Appendix 1) of the desired price dynamics and others being randomly chosen days from the set of days that were in the pool for consideration as training data. A big problem when working with models of financial prediction is the estimation of out-of-sample performance for the obtained models or trading rules. In particular, it is very easy to jump to conclusions regarding trading rules that exhibit extremely profitable behavior on certain training data. This phenomenon is sometimes referred to as *over fitting.* When not enough validation done

over out-of-sample data, the parameters are tuned finely to the training data, and the systems' general behavior is not very good.

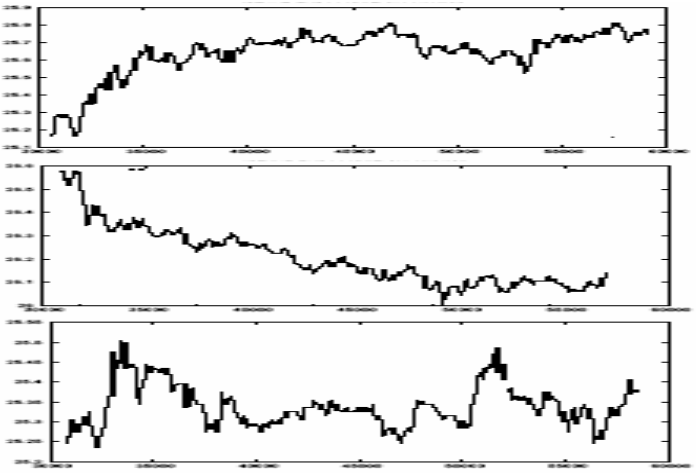


Figure 3.5: Some representative price dynamics (Appendix 1 for details)

3.2 GENETIC PROGRAM AGENT (GPA)

The approach in this section uses a genetic programming methodology much like the design in [30]. In a number of ways, the design of this agent is very similar to the one in section 3.1.1. Genetic programs themselves are extensions of the basic GA, and involve a number of the same evolutionary methods. A binary string (much like the one used in section 3.1.1 in the design of the GA) is the starting point in using GP to solve the problem at hand. Binary strings are an effective form of representation since complex statements of Boolean logic as well as numerical values of parameters can be represented in this form. For example, statements such as:

If ((Function 1)=True AND *(Function 2) = False)*OR*(Function 3)=True;*

Sell @ sellprice (ordervolume)

|

|

Else If (Function 2)=False

Buy @ buyprice (ordervolume)

can be represented quite easily using a binary bit string. The primary difference between this approach and the GAA is the allowance for growth of trading strategies based on combination of rules and thus a variable number of component rules, and the use of Boolean operators as combiners rather than the 'weighted majority' design in the GAA. The use of GP allows for optimized strategies based on single rules as well as a fixed number of chosen indicators. In a sense, the solution space of a GA is a subset of that of a GP. Trading strategies are constructed by allowing the genetic selection engine to combine the component indicator rules with Boolean operators. Strategies are once again split into *buy* and *sell* rules (and are suffixed by 'b' and 's' respectively). When a *buy* or *sell* rule gives a buy or sell signal, the rule is evaluated and determined to be *True* or *False*. For example, when a *sell* rule is *true*, it would imply that the indicator condition is satisfied. In the case of the moving averages strategy (Section 3.1.1), it might imply that *MA_1 is greater than MA_2 + Threshold*. If this rule were *false*, then it would indicate that *MA_1 is not greater than MA_2 + Threshold*.

Let us take the example strategy statement,

If ((Function 1s)=True AND *(Function 2s) = False)*OR*(Function 3s)=True;*

Sell @ sellprice (ordervolume)

|

|

|

If (Function 2b)=True

Buy @ buyprice (ordervolume)

The rules *1s* and *3s*, etc are sell rules that are used as component strategies and possible nodes in the GP decision tree (section 2.3). There are corresponding buy rules (*2b*) that decides the buy criteria. In each case, the GP has the potential to choose from buy and sell rules based on four technical indicators defined in section 3.1.1 (topic *II*). The Boolean operators AND, OR and XOR are used to compose these buy and sell rules. Finally, as a cash and share position management, we use the multiple model control mechanism, like in GAA. The order price is similar to the price used in GAA and the

order volume in GPA was throughout this thesis is 125 – this value determined empirically over 10 sample days. We abandoned attempts to include volume as a tuning factor in this experiment, in order to simplify the design. The structure of the strategy as well as the binary string has certain changes from the representation in GAA (Figure 3.6). We have Boolean connectors and the use of *rule in use* bits that tell us whether a certain rule is selected for use or not.

In Figure 3.7, we show how such a rule structure like the one in Figure 3.6 translates to a binary string. Each indicator has a particular *bit* that reflects that it is either true or false by indicating 1 or 0, respectively. Also, each indicator pair has a Boolean connector - AND, OR, XOR - represented by 00, 01 and 10, respectively. The last part of the string indicates which indicators are to be ignored. This allows strategies containing variable numbers of indicators to be represented without substantial change in design from the GAA. Note that although the *buy* and *sell* rules are dependent on two and three indicators, respectively, they are of the same length.

BUY	Rule 1		Rule 2		Rule 3		Rule 4	Rule1 Used?	Rule2 Used?	Rule3 Used?	Rule4 Used?
	1 True	00 AND	1 True	01 OR	0 False	00 AND	1 True	1 Yes	0 No	1 Yes	0 No

SELL	Rule 1		Rule 2		Rule 3		Rule 4	Rule1 Used?	Rule2 Used?	Rule3 Used?	Rule4 Used?
	1 True	00 AND	1 True	01 OR	0 False	10 XOR	1 True	1 Yes	1 Yes	1 Yes	0 No

Figure 3.6: Structure of buy and sell bit strings that populate the GP

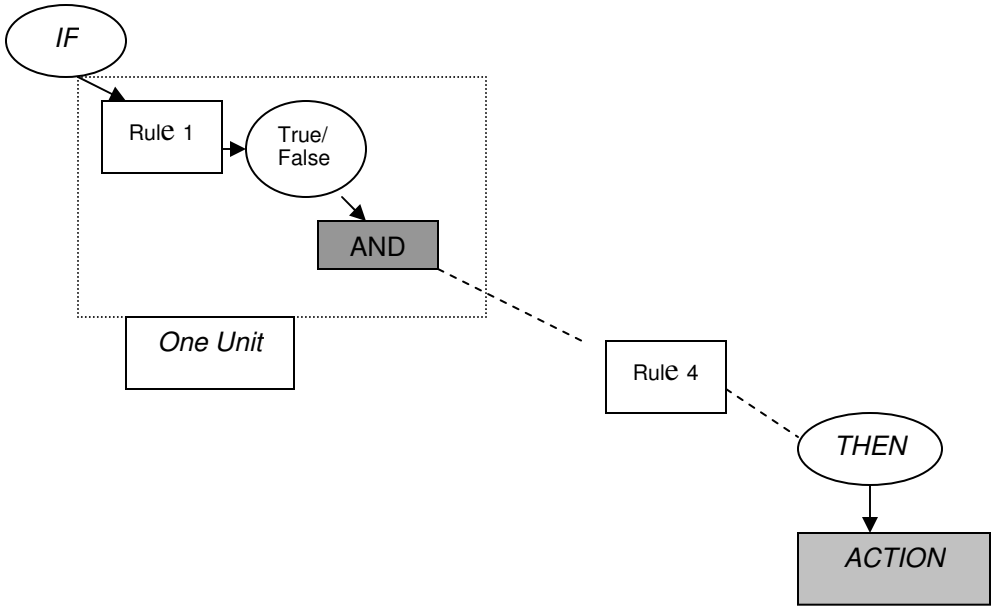


Figure 3.7: Structure of the basic GPA strategy

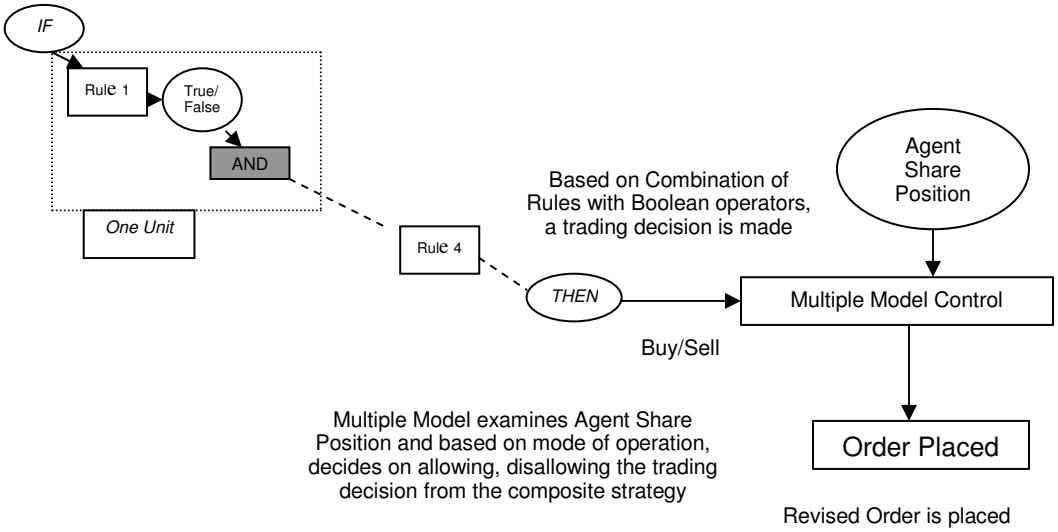


Figure 3.8: Overview of working of the GP agent

Each generation of evolving strategies in the GP follows the same steps (population initialization, fitness calculation, crossover and mutation) as that of the GA (section 3.1.1) and the mechanics of these steps remain the same. Additionally, the training process remains the same. Figure 3.8 shows how the change in this strategy is only in the ME phase of the overall design, and the APE phase remains as it was in the GAA.

Chapter 4. Results and Analysis

This chapter is divided into two segments. The first segment contains experiments, results and analysis with the primary focus being on developmental results, and exploration of various schemes of optimization of our basic algorithm. The second segment contains results and analysis of our composite strategy in competition scenarios with other agents.

4.1 Design of Experiments

Controlled experiments were performed to evaluate the evolutionary agents individually. This selection process was followed by competitive experiments to validate the performance of these evolutionary agents in joint simulations. The training days were chosen to fairly represent different price dynamics (Figure 3.5). With a view to testing the strategies in various environments, an effort was made to include different price dynamics in the test set of days as well. The experimental test dates were chosen from two distinct periods of time, one around December 2003 and the other around April 2004. In addition to tests performed at various stages of development of the agents (in order to evaluate certain hypotheses that we made earlier), we performed controlled, structured experiments in a competitive environment with other agents whose underlying strategies differed from our evolutionary agents as well as between themselves.

Evolutionary algorithms involve a fitness function (which is optimized) to arrive at a solution or set of solutions that are 'superior' to the explored potential solutions in the search space. However, a change in the fitness function could cause a change in the 'fitness' of the solution, and it may no longer be superior. Earlier, we looked at the *Sharpe* and *Modified Sortino* ratios as validation criteria. We hypothesized that using these measures as fitness functions in comparison tests could shed some light on the issue and provide interesting results. A matrix of tests (Table 4.1) was performed in an effort to perform this study.

Fitness Function	Evaluation Criteria		
		Sharpe Ratio	Modified Sortino Ratio
	Sharpe Ratio	X	X
	Modified Sortino Ratio	X	X

Table 4.1: Matrix of tests to be performed in competition with other agents

Unwinding, a rigid rule to enforce that the share holdings of the agent at the end of the day is zero, was decided to be a key necessity in the competitive tests. However, since the multiple model includes an effort to unwind, no additional rules were included in the individual tests. The final cash score, for the *individual evaluation of agents* (section 4.2) was computed to be the sum of cash value and shares valued at closing price. This modification was made since we use some aspects of our agent design as *partial* agents – and evaluate their performance against the complete agents. For example, we compare the agents without multiple model with the complete GAA and GPA, respectively. In this case, the multiple model, which is used to control share position and encourage unwinding, is absent from the *no multiple model* versions. This may put them at a disadvantage if the criteria of evaluation included penalties for not unwinding. In later sections, when we compare the evolutionary agents with other complete agents, we include the penalty for not unwinding one's share position.

4.2 EVALUATION OF INDIVIDUAL AGENTS

In the tests in this section, we use *Sharpe* ratio alone as the fitness function, as well as evaluation criteria. We compare the agent's performance against the component strategies running alone, with an unoptimized combination of indicators, and against the agents without multiple model, respectively. These tests are an effort to ascertain if there really is a benefit in using this design. Our first effort is to verify the agents' performance with their component strategies. We use the multiple model in all cases in order to maintain similar design. The four component strategies are labeled (*I1…I 4*) respectively.

Days (TE_1)	**GAA**	MAS	VS	PS	PCBS
#1	1155	1181	-1113	2166	-2592
#2	1813	679	1152	50	35
#3	955	494	1198	-2386	-3670
#4	-1391	-2102	-3558	-1130	642
#5	1164	810	-179	3451	509
#6	985	243	-1647	-1066	-120
#7	-102	-508	2267	-1218	-1501
#8	1801	722	-1147	-65	36
#9	877	-198	-1951	144	-1980
#10	-1004	-1407	1737	-75	9
#11	1104	912	-1120	110	-351
#12	1213	309	672	134	19
Avg. Profit	**714.17**	**94.58**	**-307.42**	**9.583333**	**-747**
Sharpe	**0.701**	**0.095**	**-0.177**	**0.006**	**-0.548**

Table 4.2: Comparison of (a) GAA, above and (b) GPA, below, with indicators for test set TE_1

Days (TE_1)	**GPA**	MAS	VS	PS	PCBS
#1	1447	1034	562	**1662**	-1159
#2	1006	1624	374	14	405
#3	-1364	250	-843	-1932	-1074
#4	848	-988	-1090	-899	325
#5	-765	-1285	451	1010	4
#6	1536	1129	-1315	-102	-12
#7	1501	-151	322	-1441	-1921
#8	-1712	-1148	-114	70	244
#9	318	-11	-512	501	-126
#10	109	499	2201	1	165
#11	1004	152	-900	1002	-172
#12	-104	48	1006	632	101
Avg. Profit	**318.666**	**96.083**	**11.833**	**43.166**	**-268.333**
Sharpe	**0.285**	**0.105**	**0.011**	**0.041**	**-0.371**

The training set of days used was TS_1 because it is the only set of 16 days (of the four listed in Appendix 2) that consists of all different price dynamics and does not favor any one of them. For experimentation, the test set of days used were test set TE_1 and TE_2 (Appendix 2). Running the experiment on two test sets is a measure to see if the performance superiority or inferiority of any of the competing agents is not a fluke (or a rare slip-up). With this experiment we aim to verify if the composite agents are indeed superior in performance to the component indicators. If they are not substantially better in performance over many trading days, then it could imply that our design is not necessarily a profitable one, or that the specific parameters chosen and optimization algorithm needs to be changed. The results (Table 4.2) show that GAA and the GPA (in independent tests) outperformed each of the component strategies in both test cases - an important result in support of the composed strategies. Even within the component strategies, we can see that there is quite a bit of variability between the various strategies' performance, indicating that it may be useful to include different weights for the various indicator suggestions.

Days (TE_2)	**GAA**	MAS	VS	PS	PCBS
#1	281	-372	113	-1249	-1010
#2	-1412	138	1214	1567	335
#3	1801	1021	984	-431	-1367
#4	128	1991	-3558	1419	1599
#5	1441	81	179	-1132	64
#6	1013	1210	1547	191	-120
#7	630	-1223	1067	-1021	-1200
#8	1362	1031	-1147	-429	102
#9	-376	72	351	2457	-1889
#10	-1075	-2141	1737	-899	55
#11	-121	-224	-1120	-2214	-531
#12	1492	1201	672	-1293	199
Avg. Profit	**430.33**	**232.08**	**169.91**	**-252.833**	**-313.583**
Sharpe	**0.411**	**0.201**	**0.114**	**-0.181**	**-0.333**

Table 4.2: (c) Comparison of GAA with indicators for test set TE_2

Days (TE_2)	**GPA**	MAS	VS	PS	PCBS
#1	1102	-331	1094	1210	657
#2	821	1099	-1102	712	332
#3	1009	954	810	-1109	-1982
#4	-532	1002	243	303	1023
#5	908	-912	-208	1688	-16
#6	-1604	-112	722	-878	1102
#7	-199	58	-198	-1809	-1621
#8	1321	872	-1407	188	921
#9	188	18	940	248	-2211
#10	-901	-1704	-1101	-21	-556
#11	1121	775	114	110	-812
#12	663	809	232	312	91
Avg. Profit	**324.75**	**210.6667**	**11.58333**	**79.5**	**-256**
Sharpe	**0.346**	**0.24**	**0.013**	**0.082**	**-0.217**

Table 4.2: (d) Comparison of GPA with indicators for test set TE_2

This lends support to our initial hypothesis that technical indicators, when used in combination, do not lend suggestions of equal power. This leads us to believe we'd be better off with a *weighted majority* schema. In order to verify this in the case of GAA, we compare the use of tuned weights against fixed and equal weights, for two different test sets - TE_1 and TE_2 (Appendix 2). The training set was TS_1 again owing to the fact that it is the only training set with all representative days (Appendix 1). The results of this comparison are tabulated in Table 4.3.We may venture to explain the advantage that tuned agent has with the following:

- Equal weights would imply that each of these indicators were equally confident when they gave a buy or sell recommendation *at each time step*. This may not be the case. For example, a price breakout may be more of a 'sure bet' suggesting a trend than the simple price check. So, the weights should be allowed to decide accordingly.

- Different weights for buy and sell sides accommodate the contingency that an indicator may be more *confident* of a buy signal as opposed to a sell signal, or vice versa.

It might have been a better strategy to include the entire suggestion from the indicator strategies, i.e. take the suggestion as well as volume from the indicators, and average it in some way to get the desired trading volume. However, this would only be useful if the volumes we obtained were themselves optimized. This optimization would introduce further computation, something we've tried to avoid all along. In the event, the fact that the parameters we use for our indicator strategies are hand-picked means that it is not very useful to use these values to get a final trading volume. We decide to extract only the trading *suggestion* from the indicators, and use the *confidence* of this suggestion (sum of weights) to obtain the trading volume.

Days (TE_1)	**GAA**	Equal Weights
#1	1155	966
#2	1813	489
#3	955	-505
#4	-1391	-1128
#5	1164	-1021
#6	985	1002
#7	-102	881
#8	1801	-1101
#9	877	908
#10	-1004	-765
#11	1104	**1232**
#12	1213	1177
Avg. Profit	**714.17**	**177.9167**
Sharpe	**0.701**	**0.18**

Days (TE_2)	**GAA**	Equal Weights
#1	281	112
#2	-1412	723
#3	1801	-1121
#4	128	-998
#5	1441	-64
#6	1013	16
#7	630	-1101
#8	1362	1449
#9	-376	-19
#10	-1075	102
#11	-121	-1
#12	1492	749
Avg. Profit	**430.33**	**-12.75**
Sharpe	**0.411**	**-0.016**

Table 4.3: Comparison of tuned weights and equal weights for test sets TE_1 and TE_2

The above tests indicated that our initial hypothesis regarding the benefit of using technical indicators in a weighted combination scheme like in GAA, had some merit to it. To further explore this hypothesis, we isolated four different sets of training days to train this agent over. These days had been chosen such that a majority of the days had different price dynamics from the other sets of days. This would allow us to isolate the difference in the solution weights over different scenarios. The four sets of days chosen had *majority monotonic, majority mean reverting, majority other* and *no majority* price dynamics and corresponded to the sets TS_2, TS_3, TS_4, and TS_1 (Appendix 2), respectively. The result of this test proved very encouraging and supported our hypothesis. In Figure 4.1 we observe that the weights are uneven and favor some of the indicators more than the others. In addition, we notice that there is a change in weights over the different training sets. Both of these results concur with our hypothesis for this design.

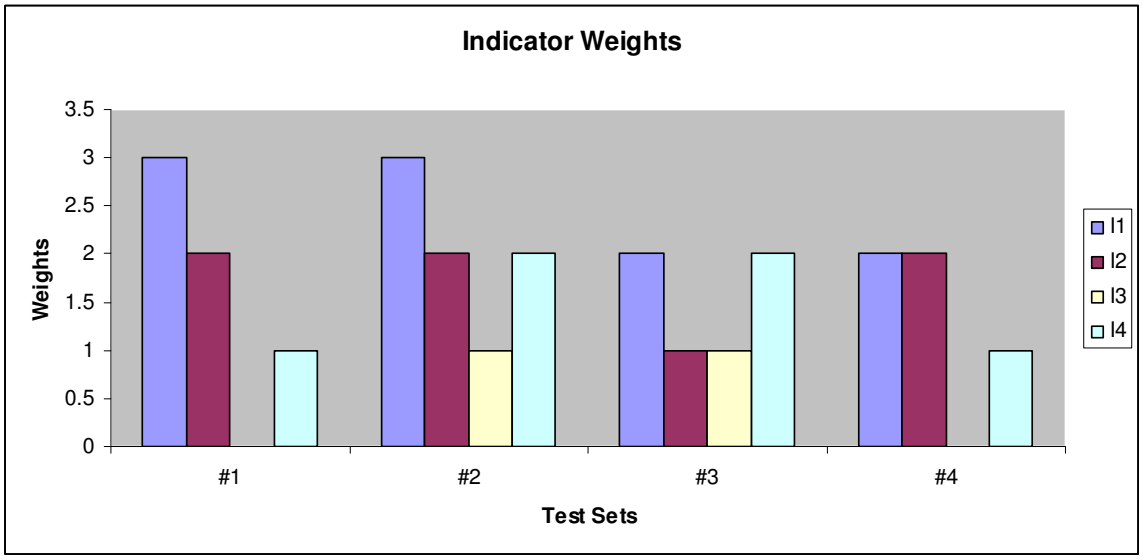


Figure 4.1: Weights of indicators for training sets TS_1, TS_2, TS_3, and TS_4

On testing the agents tuned to these different training sets (on test set TE_1), we notice that the weights that were tuned to TS_1 gave us the best performance on TE_1, (Table 4.4), as expected. TS_1 contains all price dynamics and is not favored towards any particular one of them. The agents whose weights were tuned over TS_2, TS_3 and TS_4 were profitable

(probably because these training sets do contain days of all price dynamics, although they are largely biased towards particular price dynamics), but lagged in performance to the agent whose weights were tuned to TS_1. The number of training and test data available are so few that no statistically significant conclusion can be made from these. We just use these results as guidelines to the agents' behavior over larger (more complete datasets), and to try and glean some qualitative information out of them. Table 4.4 only reflects the Sharpe ratio, and we performed this test only on TE_1. The reason for performing only the one test is that our primary aim with this experiment was to verify if the weights were indeed different for various training sets, and if the appropriate choice of training sets did affect the performance of the agent over test data. Further verification and an in-depth look at performance of the agents with other test sets are included in later sections.

Training set	Sharpe Ratio (over test set TE_1)
TS_1	0.377
TS_2	-0.181
TS_3	0.142
TS_4	0.212

Table 4.4: Performance of agents tuned on different training sets on test set TE_1

So far, we have verified the utility of using a *combination* of indicators as opposed to using them individually, and found that there is indeed an advantage in using a *weighted* combination as opposed to a simple addition or averaging. It now remains to be seen if there is indeed any advantage in using the multiple model mechanism to control share position needs to be explored. In the event that there is no substantial performance improvement using this mechanism, we could eliminate this aspect and simplify the algorithm. A competing strategy we used for this test was the composite strategy without the multiple model. In both GAA and GPA, the multiple model mechanism was eliminated, and these stripped agents were tested with the complete agents. The training set used was TS_1 (the only training set with uniform number of different price dynamics)

and the test set of days used was TE_1 (the test set we use for all tests in this section). From Table 4.5, we see that the evolutionary agents outperformed the ones without multiple models.

Test Set TE_1	Sharpe Ratio	*Test Set* TE_1	Sharpe Ratio
GAA	**0.701**	**GPA**	**0.133**
No Multiple Model	0.255	No Multiple Model	-0.101

Table 4.5: Comparison of (a) GAA and (b) GPA with a *no multiple model* agent

A curious observation was that in the absence of the multiple model, the strategy tended to trade lower volumes and allotted higher weights to indicator strategies that were *safe* (that had higher thresholds). Figure 4.2 reflects this difference in volume of trades for one of the trading days. A possible explanation is that in the presence of the multiple model, the agent is willing to take a riskier position, with the confidence that it will be *led* back to safety.

There are two ways of optimizing the *Sharpe ratio* – increasing profit everyday, or decreasing variance. Without multiple model mechanism, the optimization is possibly favored with a lower variance and lower profit. With multiple model, the profit is higher (due to higher volume of trades), but the variance is also higher. This indicates a slightly more aggressive, but more profitable strategy. In this experiment, we limited the experiments to only one test set of data (TE_1). As we mentioned earlier, in these experiments, we aim only to look at general behavior of the agents, and don't aim to prove anything with any significant statistical confidence. Moreover, we test the agents in competitive environments in later sections. Finally, we compare the performance of each of these agents independently with SOBI (section 2.2.1), a baseline agent provided by the PLAT group. The price dynamics of the test sets we chose were monotonically increasing, monotonically decreasing, mean reverting and no majority (all from TE_1), respectively. The tests were performed on certain hand picked days and aim only to verify the performance of the agents over separate days with different price dynamics.

Verification over a larger set of days and evaluation using Sharpe and Modified Sortino Ratios follow in later sections, where SOBI was included as a competitive agent. We consider the raw cash measure for the days below as a performance measure (with the closing price sale of all excess shares at the end of the day, or closing price purchase of all deficit shares).

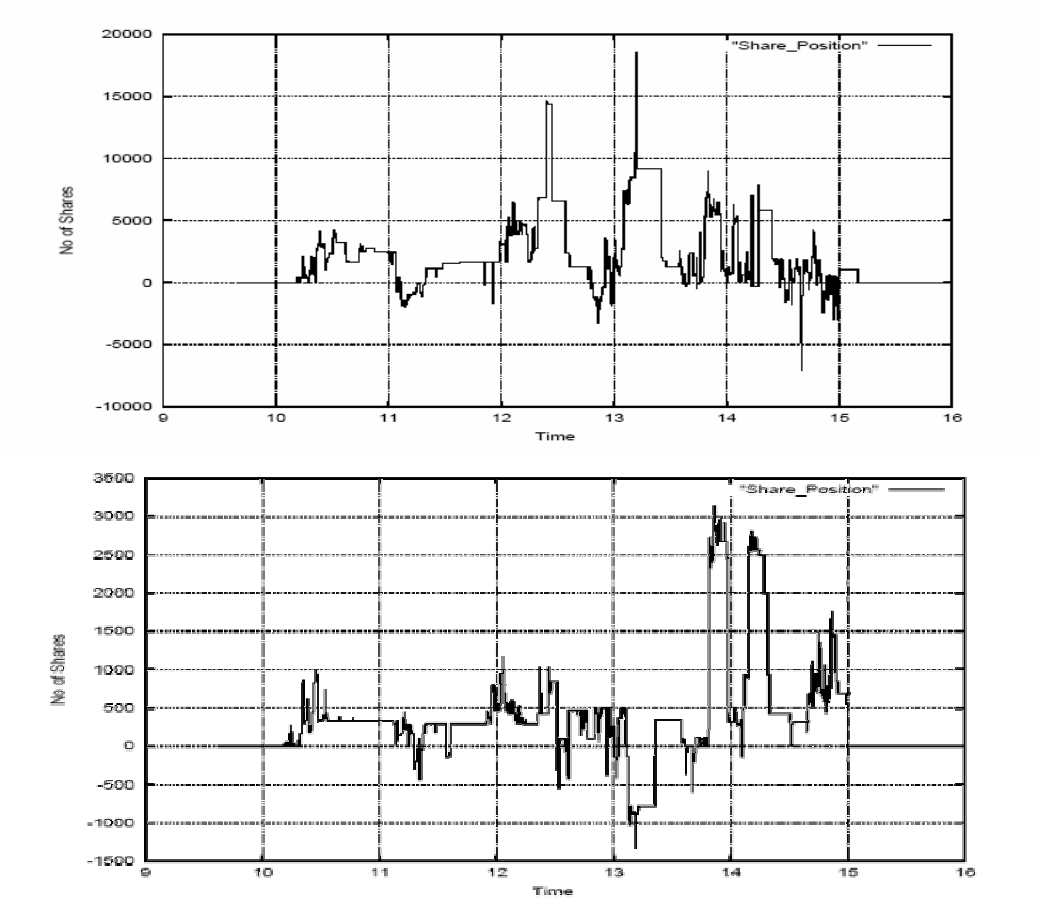


Figure 4.2: Volumes of trade on a typical trading day when comparing GAA with multiple model (above) and without (below). Notice the scale of the plots.

From Table 4.6, we find encouraging results from both the GAA and the GPA – each outperforming SOBI on five of the seven days. On days of monotonic variation, both the evolutionary algorithms showed promising results, GAA ending in the black on 3 of the four days and GPA on two of them, but averaging positive cash over these days. The days

when the price was mean reverting was closer, and on one of these days, SOBI outperformed GPA. It shows that given the right circumstances, any strategy can prove profitable on some days. While the cumulative results above do indicate that GAA as well as GPA outperformed SOBI, we need to explore their performance further – in more realistic economies (with competing agents).

	Cash Measures		Cash Measures	
Price Dynamics	GAA	SOBI	GPA	SOBI
Increasing	1401	1673	608	5
Increasing	882	-12340	-132	-11021
Decreasing	571	10211	810	8982
Decreasing	-11	-11059	-208	146
Mean Reverting	2133	1912	621	4003
Mean Reverting	1514	-14402	102	-13106
Other	1224	-30023	1019	-25001

Table 4.6: Individual agent performance (cash measure) of (a) GAA and (b) GPA with SOBI on select 'representative' days.

4.3 JOINT SIMULATION

In this section, we examine these agents' performance in joint simulations (when they were allowed to run against each other as well as other agents) in slightly more realistic economies, with numerous different strategies. As opposed to earlier tests, when the evolutionary agents were used in targeted experiments with a view to testing various aspects of their design, our aim in this section is to test these agents in an environment where the other agents have different strategies, are competitive and are all aiming to be profitable. In this experiment, we used TS_1 as the training set and TE_2 as the test set of days. As we had earlier tested these agents in various scenarios (section 4.2) using test set TE_1, we decided to use TE_2 in this experiment, with a view to testing the agents over a new set of test days. The training set we used was TS_1 again, as it is the only set with uniform number of days with different price dynamics. Table 4.7 below shows the results

of the first joint simulation we performed. In addition to GAA and GPA, we use competing agents SOBI, Market Maker (MM) and Volume-based agent (VBA). We discussed these competing agents in Section 2.2. However, our aim in this section is only to compare the performance of the GAA and GPA agents and evaluate the usefulness of the *Modified Sortino Ratio* (MSR) as a fitness function in our design. We evaluate these agents in a competitive test in later sections. Columns 1 and 2 of Table 4.7 display the result of tests performed on GAA and GPA when they were tuned with *Sharpe ratio* as the fitness function in training phase. Columns 3 and 4 of the table show the results of similar tests performed on the evolutionary agents with *Modified Sortino Ratio* as the fitness function. We also evaluate the agents below using the *Sharpe* and *Modified Sortino ratios*, and additionally the raw profit (cash) score, as performance criteria; in order to verify our hypothesis that the agents tuned to maximize profits and avoid only negative volatility would do better than those which aimed to reduce all volatility. We used the standard PLAT scoring policy and rules (discussed in Section 2.1.4), and enforce unwinding penalties (in accordance with the rules imposed by the PLAT group in earlier competitions).

At this point, as a means of evaluating the improvement in performance of agent, we introduce a measure called the *MSR to Sharpe ratio*. This is the ratio of the values of MSR and Sharpe ratios for a given column in our table. We see that GAA and GPA (tuned with Sharpe ratio) showed values of 2.34 and 2.23 respectively, for this measure. This value for GAA and GPA tuned with MSR was 5.12 and 2.49 respectively. We observed that the agents tuned with MSR not only showed higher MSR values, but also Sharpe ratios not too far below the SR-tuned agents. The difference between MSR and Sharpe ratios was most stark in the case of GAA. This, coupled with the fact that the Sharpe ratio was not too far off for GAA-MSR as compared to GAA-SR, is a good indicator of the usefulness of the new fitness function in GAA. Also, from Figure 4.3 and Table 4.7, we notice that the average profit as well as maximum profit was also higher for GAA tuned with MSR. In the case of GPA, the MSR version did perform better than the SR version in the MSR evaluation (and was very close in Sharpe ratio too), but the

difference was not very much (as is evident from the similar MSR to Sharpe ratio values). In general, we observe that the agents tuned with MSR as fitness function showed higher average profits as well as higher total profit over the set of out-of-sample test days, presumably since they did not have to worry about volatility in the positive. From the table, we see that maximum profit over the period improved from 2536 to 7924 in GAA and from 2034 to 3939 in GPA, when fitness function changed from SR to MSR. Average profit similarly went up from 796 to 1773 for GAA and 415 to 660 for GPA.

Test Days (TE_2)	Sharpe ratio as fitness function		MSR as fitness function	
	GAA	GPA	GAA	GPA
#1	1008	1189	1250	1924
#2	**2536**	679	**7924**	**3939**
#3	1036	494	1251	1333
#4	-1447	-1102	-1512	-118
#5	1364	1210	1285	162
#6	855	331	2148	242
#7	175	-108	-499	-1253
#8	1692	735	4034	211
#9	715	-1123	598	1133
#10	-744	-450	-986	-1863
#11	1221	**2034**	2162	1892
#12	1145	1098	3624	322
Avg. Profit	**796.3333**	**415.5833**	**1773.25**	**660.3333**
Sharpe Ratio	**0.751357**	**0.431729**	**0.691213**	**0.43023**
MSR	**1.761815**	**0.964018**	**3.540813**	**1.0708**
MSR/Sharpe	**2.344844**	**2.232922**	**5.122612**	**2.4889**

Table 4.7: Joint simulation with Sharpe ratio and MSR used as fitness functions for evolutionary algorithms and as means of evaluation

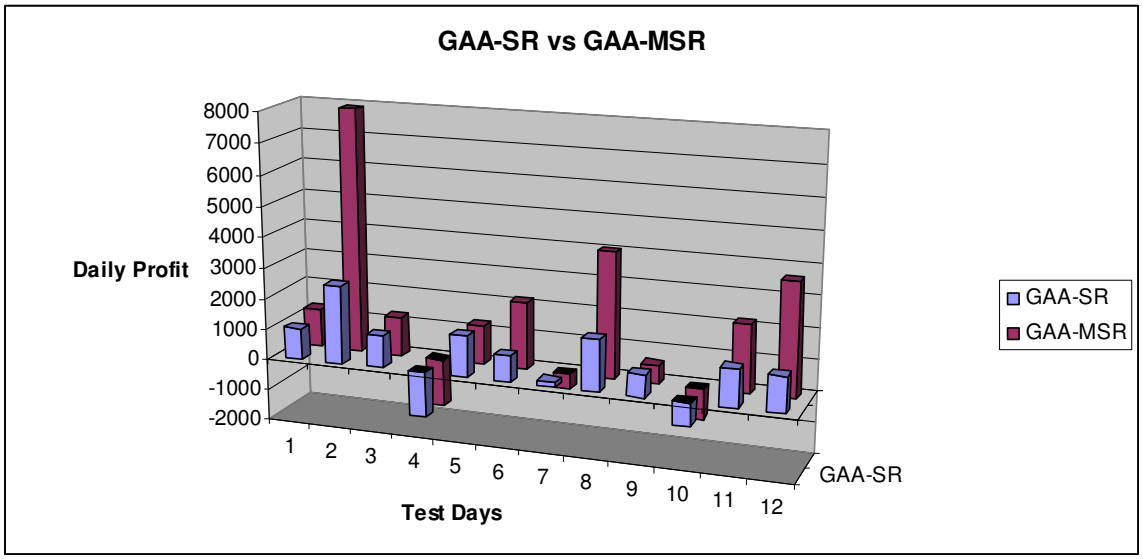


Figure 4.3(a): Comparison of GAA-SR and GAA-MSR performance (test set TE_2)

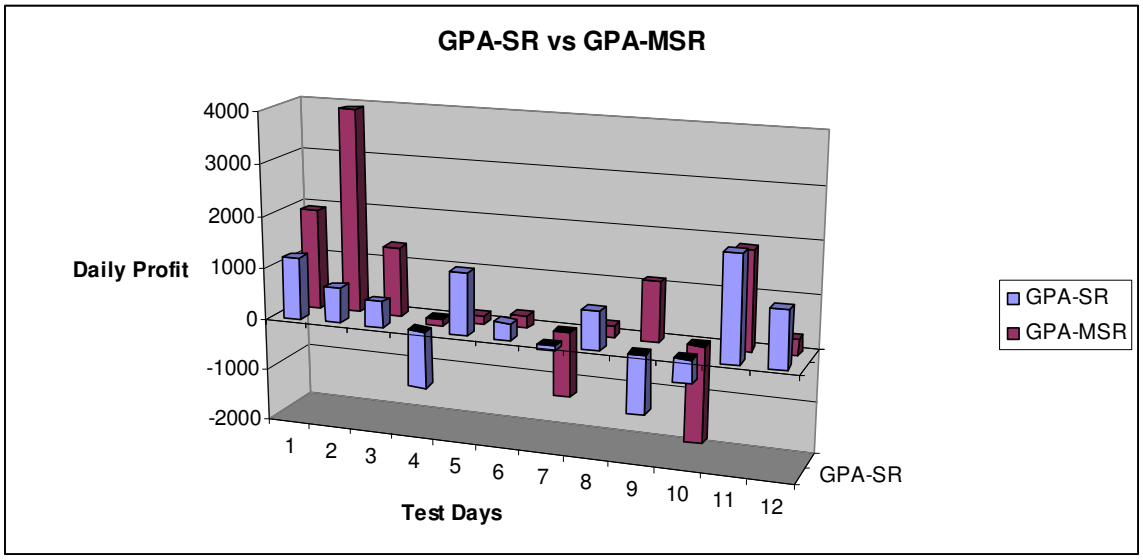


Figure 4.3(b): Comparison of GPA-SR and GPA-MSR performance (test set TE_2)

The comparison between SR and MSR shows that the use of MSR as fitness function in our optimization procedure shows improved performance, not only when the criteria of evaluation is MSR, but also in terms of average and maximum profit. When MSR was used as fitness function, these agents also ranked very close to the performance of the

SR-tuned agents, even when SR was used to evaluate these agents. Earlier, we had hypothesized that the elimination of penalty for positive volatility would help improve profitability, as we were penalizing agents for making large amounts of profits on a trading day as much as we were penalizing them for losing large amounts on a day (through the use of standard deviation). The results in this section validate our hypothesis, and indicate that the use of better fitness functions, like MSR (which penalizes only money losing behavior) may be a key factor in designing evolutionary agents such as the ones in this thesis.

4.4 COMPETITIVE TESTS WITH OTHER AGENTS

In competitive tests, we use all four agents (GAA and GPA, each tuned with Sharpe ratio and MSR) from the previous section, in addition to which we use SOBI, MM and Multiple Model Agent (MuMo)[10a] – the last two were winners in two previous competitions held in December 2003 and April 2004 (Appendix 3) respectively, and were used to benchmark the performance of our evolutionary algorithms against competitive agents. For the sake of readability, the GAA with Sharpe ratio as fitness function was labeled GAA-SR and that with MSR as fitness function was labeled GAA-MSR. The GPA counterparts were labeled GPA-SR and GPA-MSR respectively. The training set for this run was TS_1 again owing to the unbiased distribution of price dynamics among the days in this set. To test the agents in a competitive test with successful agents from past competitions, and to do so on days that were not used in training or tests before, we use TE_3 (Appendix 2) as the test set. In this test, we did not use other agents such as the individual indicator strategies (section 3.1) since we had already tested them over two datasets in previous tests (section 4.2). Also, we aimed to limit the number of agents used in the test so computation as well as documentation would be easier. Apart from the changes discussed above, the rules remained the same as in the case of joint simulation (section 4.3). Table 4.8 below lays out the results of this experiment.

The results of this experiment show that the performance of the evolutionary agents was fairly competitive with the best agents from previous competitions (MM and MuMo) and

substantially better than SOBI. Let us look at some comparisons that stand out from observation of Table 4.8. For a clearer view and to make comparisons easier, the reader is urged to refer Figure 4.4, which summarizes the information in plots.

Days (TE_3)	GAA-SR	GAA-MSR	GPA-SR	GPA-MSR	MM	MuMo	SOBI
#1	**2526**	4655	1278	**4416**	223	2891	4133
#2	1249	2177	1045	492	312	3445	1698
#3	1567	2765	242	-253	184	1717	-2753
#4	82	-545	-1694	-130	271	1433	-7028
#5	1900	2402	1376	141	538	2037	-12182
#6	-132	1100	-376	49	-241	-141	-4422
#7	1145	2601	1441	2011	135	2465	481
#8	1112	5500	1141	1216	-12	1850	1233
#9	1429	2802	630	1134	**656**	2928	4399
#10	2457	**7975**	**1707**	1175	385	**5229**	12180
#11	-899	-1100	-1376	-755	142	-1349	-3405
#12	-1214	-1370	-775	-1076	461	-1562	-14092
#13	-1029	184	-102	125	122	1307	**12333**
#14	1723	4213	1090	2212	224	2509	-10120
#15	-1038	102	-221	-113	-213	-1338	231
Avg. Profit	**725.2**	**2230.733**	**360.4**	**709.6**	**212.4**	**1561.4**	**1154.27**
Sharpe	**0.5521**	**0.851719**	**0.335342**	**0.509728**	**0.854144**	**0.807884**	**0.14735**
MSR	**1.517778**	**5.007865**	**0.658961**	**2.196996**	**2.574284**	**2.670785**	**0.18029**

Table 4.8: Test of evolutionary agents' performance with competitive agents

As expected, GAA-MSR and GPA-MSR outperformed GAA-SR and GPA-SR respectively, in the evaluation criteria that favored them (MSR). Most interesting, however, was that the average profit was higher for both the agents' MSR versions than the SR ones. Also, the maximum profit (over all days) for each of the MSR agents was higher than the SR counterparts. This is an encouraging result, since it supports our

decision to not only evaluate the agents differently from previous competitions, but also to factor this into the agents' behavior to increase average profit.

MM outperformed all the evolutionary agents (GAA-SR, GAA-MSR, GPA-SR, GPA-MSR) in the Sharpe ratio evaluation. However, when MSR evaluation was considered, the agents (particularly the ones with MSR as fitness function) were much closer in performance to MM (GAA-MSR was much better than MM) and the average profit of GAA-MSR as well as GPA-MSR was greater than that of MM. GAA-MSR had a higher MSR than MM and GPA-MSR was only just beaten in this regard. Again, this is an encouraging result in support of our designs. MuMo outperformed GPA-SR in both SR and MSR evaluations. However, GAA-MSR managed to outperform MuMo in MSR as well as SR evaluations and GAA-SR also outperformed MM in MSR evaluation, barely losing out in SR.

Overall, the above results can be summarized by saying that the MSR versions of the evolutionary agents performed well and were extremely competitive with the other leading agents. Also, the GAA strategy seemed more useful than the GPA strategy, possibly because the design of GPA needs a larger pool of indicators to choose from. The results above suggest that the evolutionary design was fairly successful as was the incorporation of MSR. An important observation is the superior performance of the evolutionary agents when tuned by MSR instead of SR – especially in the weighted majority case of GAA. A curious aspect of the live competition results in April 2004 was that the GA agent used then (GAA-SR) lost out to MuMo, which implemented a basic moving average strategy within the multiple model structure to trade. It raised the question as to whether we were adding additional complexity for no reason. As a hypothesis, this failure was attributed to the fact that tuning the agent with Sharpe ratio as a fitness function may have been the wrong choice, as it may have imposed an upper bound on trading profits on a given day to reduce volatility. To explore this possibility, we introduced MSR as a measure limiting only downside volatility. This proved very useful indeed, and contributes to this thesis, a very important result. It also strengthened

our view that the weighted majority approach could indeed be useful, albeit with a more sophisticated fitness function.

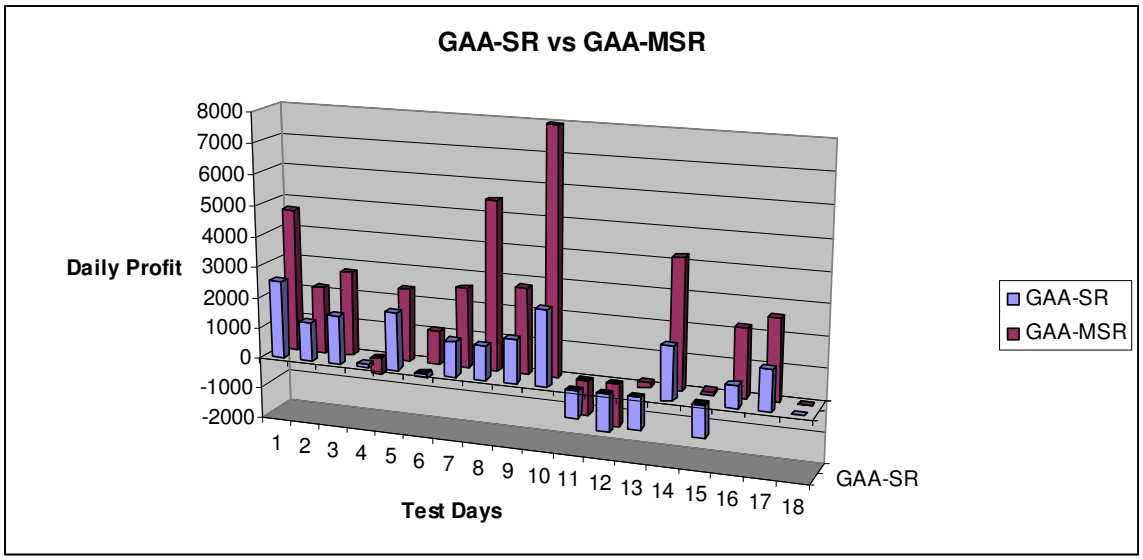


Figure 4.4(a): GAA-SR and GAA-MSR in the competitive run (test set TE_3)

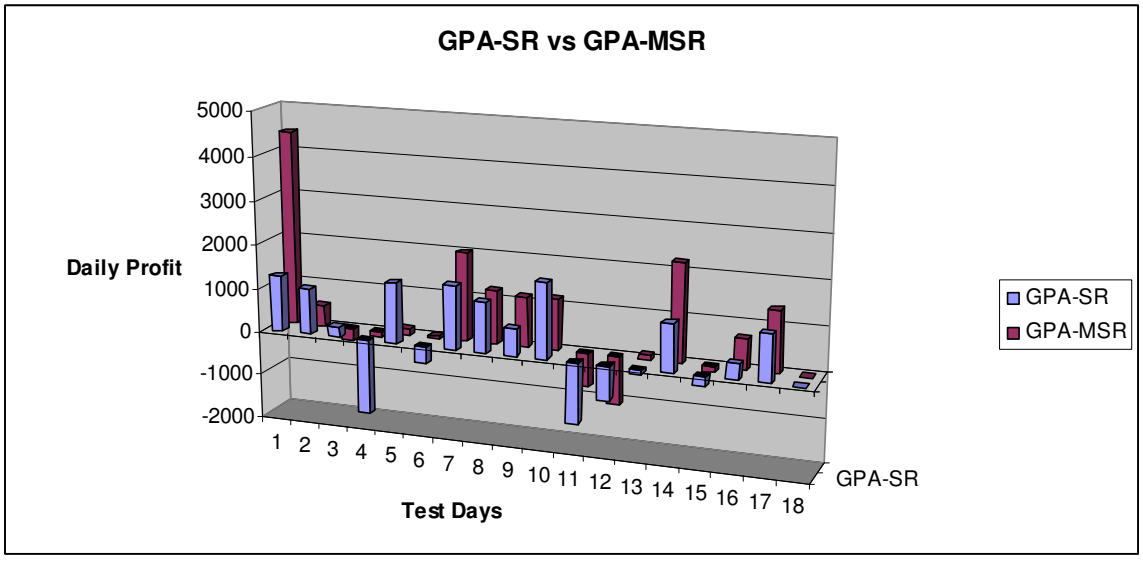


Figure 4.4(b): GPA-SR and GPA-MSR in competitive runs (test set TE_3)

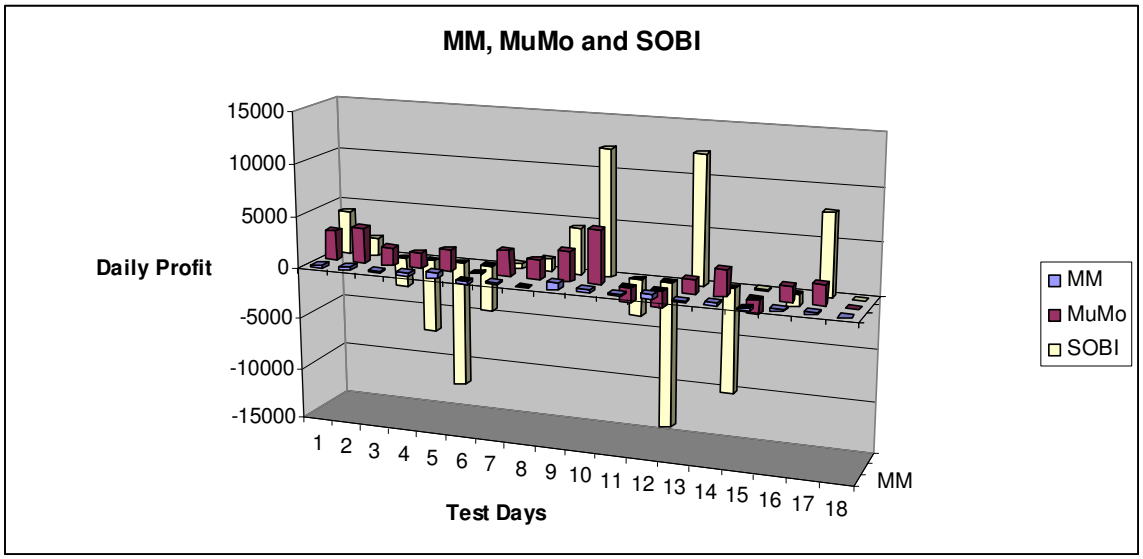


Figure 4.4(c): MM, MuMo and SOBI in competitive runs (test set TE_3)

Chapter 5. Conclusions and Future Work

In this thesis, we have explored applications of evolutionary algorithms (GA and GP) to technical trading rules in an effort to develop profitable agents for trade in the PLAT domain, as well as to provide insight into the utility of such design to automated trading scenarios. An important factor to consider is that this research was performed purely as a study of certain agent schemes and as an exploration into the use of evolutionary algorithms *in the PLAT domain.* Various limitations were imposed during the course of this work, and although PXS is more realistic than most of the simulators used in previous such studies, it is far from being realistic. The results in this thesis are strictly within the confines of the test economy and no reasonable guarantees can be made regarding its utility (as is) in actual trade markets. Our aim was to study the implications of certain design aspects in a *simulation* and the study aims to be a launch pad to more advanced and sophisticated agent designs of a similar nature.

Various studies have shown the benefits of technical trading as an effective day trading strategy. However, their utility as effective strategies when used individually or in combination but without the benefit of human 'intuition' has proven quite low. We have found in this thesis that it is possible to profit from trading technical rules when the trade entry signal is taken from combinations of indicators since this is the manner in which a technical trader would use such indicators. The above work is just a sample of what can be produced using such a system. Further adaptation techniques could include periodic re-optimization with longer and shorter periods. As was previously stated, this first test of our system aims to show that such a structure merits further work by analyzing results in a general and unoptimized framework.

In this thesis, we proposed two frameworks for combining technical trading rules in an effort to trade profitably in the PLAT domain. While the GPA design proved to be only moderately successful in tests, it might have greater utility if parameter optimization was done, especially the trading order volume. In this design, we used a fixed number

(arrived at empirically). Including volume in the bit string for a GPA-like design may be a possible solution. We did not explore this idea further, but suggest it as a possible fix. The GAA design proved much more successful and not only outperformed GPA and the baseline SOBI agent, but also beat or proved very competitive when pitted with successful agents from previous competitions in our battery of tests. We found that GAA performs better than its component indicator strategies. To test if any combination of technical rules would do, we compared our weighted majority algorithm with an agent where the component indicators were combined with each of them weighted equally. Superior performance of our weighted agents vindicated our decision to use evolutionary algorithms to optimize weights for GAA. Further, the use of multiple model share position control mechanism seemed to provide for unwinding while performing better than the basic agents without the multiple model. In further tests of the agent against competitive agents over different test sets of trading days, GAA proved to be profitable and better or as good as the most successful of existing agents in the PLAT domain.

The evolutionary agents (particularly GAA) were fairly successful, but not quite competitive with the successful PLAT agents until we used a new fitness function (MSR), that penalized only loss making volatility and not all volatility (as Sharpe ratio does). When the agents used MSR as fitness function, they proved to have improved performance including greater profitability. This leads us to believe that there is useful information in technical indicators that can be exploited, and further development and the use of carefully chosen fitness functions might mean that such a design may prove to be even more successful. This is consistent with the claims of technical analysis. The use of multiple model mechanism also proved quite effective as a control element to the strategy, allowing our agents to 'boldly' hold positions with the confidence of being shepherded back to a desirable state by this mechanism. The qualitative nature of this mechanism also appeals to intuition, and this was in keeping with our theme of using an intuitive combination of technical rules. By implementing a simple set of weights, various human trader-like behaviors could be replicated. These include deciding how

important a certain indicator is, and dropping certain indicators if they showed consistently poor performance (by turning the weight down to zero).

What is evident is that more work has to be done in areas such as bit string representation, fitness function choice and online optimization. Possible improvements include finer resolution of weights using longer bit strings, the use of more indicators, and development of more sophisticated fitness functions to include details finer than just measures of profit and deviation over many days. Other feature additions could include a method to run this optimization algorithm online (as a background process) and include training days on the fly. This would make the agent more adaptive to immediate changes and eliminate the need for time-intensive and periodic offline training.

This thesis is a small part of growing research in which computer-simulated market interactions of autonomous agents are studied and an attempt is made not only to develop a profitable trading strategy, but through these efforts, understand the working of the market itself. The thesis provides us with a few solution concepts to certain aspects of the automated trading problem, but has not been tested with any statistical significance and the results we have obtained are by no means an indication that it is ready to be deployed in the real world. It does point us (and walk us part of the way) towards possible solution ideas that may be incorporated with further work to increase profitability among automated trading agents. In a lot of ways, this thesis confirms the difficulty of automated stock trading and suggests that further exploration of heuristic solutions that may aid profitable trading is merited.

Appendix 1

MSFT Trading Prices and Price Dynamics

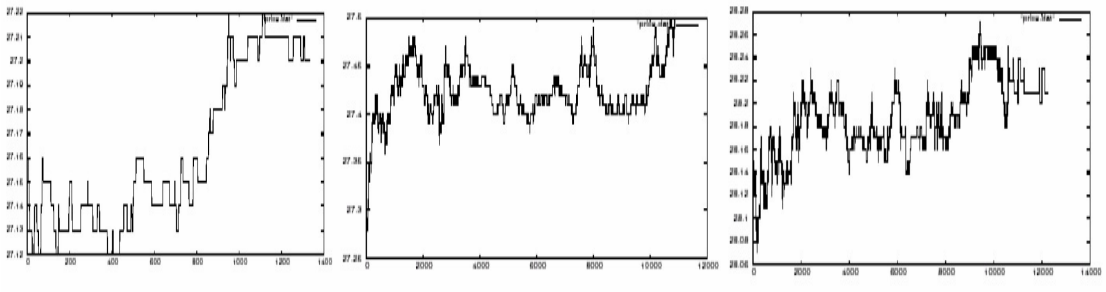
In this section, we aim to explain what we mean by *price dynamics* and briefly look at some of the prominent price dynamics that we isolate for studying agent behavior under different conditions.

High-frequency data, as we use the term, are observations taken many times a day. Price dynamics, in the context we use it in, refers to a broad characterization of this intraday data over the entire trading day. In other words, we try and fit (an approximate fit) patterns to the daily data. Of course, we do not use any modeling or curve-fitting technique, but use very broad, intuitive labeling.

Details such as opening price, closing price, high and low prices of the day – for a few sample days of each type of price dynamic we use, are listed in tables below; followed by a plot of the day's price variation. All data is of Microsoft Stock (Symbol: MSFT).

For *monotonically increasing* data, we choose days that not only ended higher than opening price, but spent most of the day increasing in price.

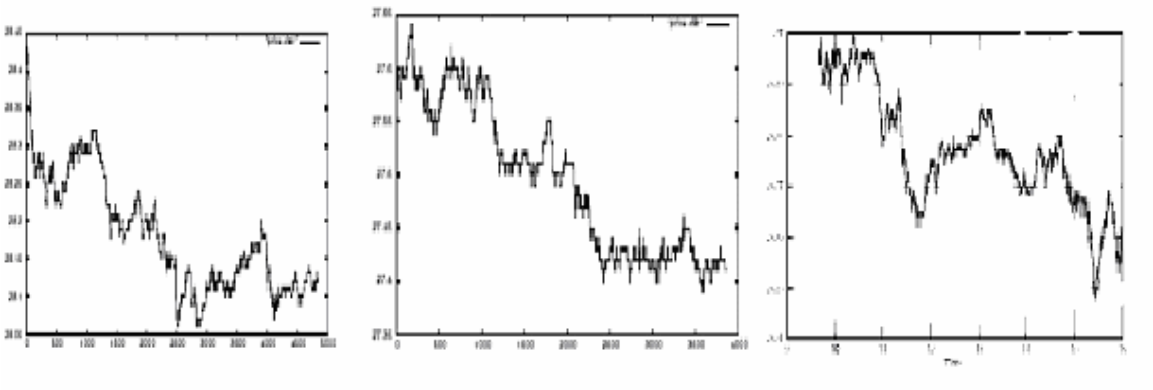
Days	Opening	High	Low	Closing
12/26/03	27.05	27.25	27.00	27.21
12/29/03	27.21	27.53	27.16	27.46
01/06/04	28.19	28.28	28.07	28.24



12/26/03 12/29/03 01/06/04

Similarly, for *monotonically decreasing* data, we choose days that end lower than the opening price, and spend most of the day decreasing in price.

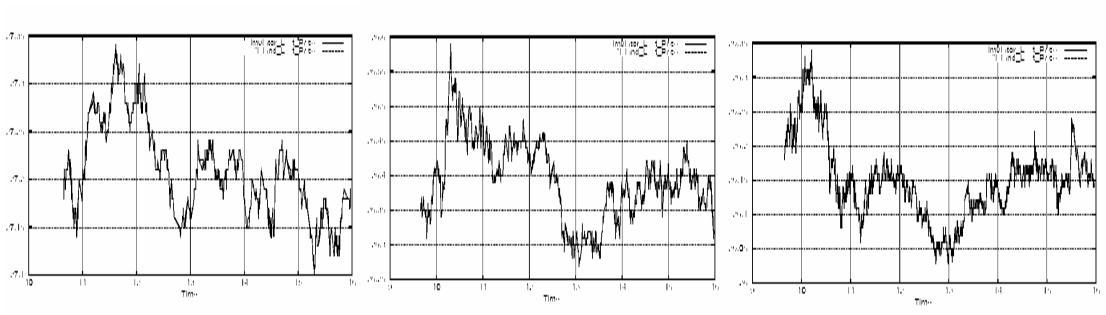
Days	Opening	High	Low	Closing
01/08/04	28.39	28.48	28.00	28.16
01/13/04	27.55	27.62	27.24	27.43
04/28/04	27.01	27.05	26.47	26.56



01/08/04 01/13/04 04/28/04

Mean reverting days imply days that ended within a small margin of the starting price (we use ± 0.05 of a dollar as the margin). Additionally, these days spend substantial amount of time on either side of the mean daily price.

Days	Opening	High	Low	Closing
04/26/04	27.45	27.55	27.10	27.44
05/05/04	26.32	26.60	26.25	26.30
05/06/04	26.16	26.34	26.03	26.12



04/28/04 05/05/04 05/06/04

All other patterns (or sub-patterns within the day) were more generally clubbed together and labeled as *other*.

A more keen method of classifying the days might help increase the accuracy of our experiments. However, owing to the effort that would need to go into it, and the fact that we are primarily interested in the broad, qualitative behavior of the agents, we chose to take the easy way out.

Appendix 2

Training and Test Data

In this section, we list the contents of the training and test sets used in our experiments.

Training Sets:

TS_1 (All representative days + others)

12/11/2003	12/15/2003	12/12/2003	12/19/2003	12/22/2003	12/24/2003
12/23/2003	04/28/2004	12/31/2003	04/29/2004	12/16/2003	
12/17/2003	12/18/2003	12/26/2003	12/29/2003	12/30/2003	

TS_2 (Majority Monotonic)

12/16/2003	01/05/2004	12/18/2003	01/06/2004	12/26/2003	01/08/2004
01/09/2004	12/29/2003	04/28/2004	12/30/2003	04/30/2004	
12/15/2003	12/11/2003	12/19/2003	12/12/2003	12/24/2003	

TS_3 (Majority Mean Reverting)

12/11/2003	12/12/2003	12/22/2003	12/23/2003	12/31/2003	04/29/2004
04/26/2004	04/27/2004	05/06/2004	05/04/2004	05/05/2004	
04/30/2004	01/15/2004	12/17/2003	05/03/2004	05/07/2004	

TS_4 (Majority Other)

05/04/2004	05/05/2004	05/06/2004	04/27/2004	12/11/2003	04/29/2004
12/22/2003	12/12/2003	12/23/2003	04/30/2004	01/16/2004	
01/12/2004	01/02/2004	12/17/2003	05/03/2004	05/07/2004	

Test Sets:

TE_1

01/12/2004	01/02/2004	12/17/2003	05/03/2004	05/07/2004	01/12/2004
04/26/2004	04/27/2004	05/06/2004	05/04/2004	05/05/2004	01/02/2004

TE_2

01/30/2004	01/29/2004	01/28/2004	01/27/2004	01/26/2004	01/23/2004
01/22/2004	01/21/2004	01/20/2004	01/07/2004	01/14/2004	01/13/2004

TE_3

06/30/2004	07/01/2004	07/02/2004	07/05/2004	07/06/2004	
07/08/2004	07/09/2004	07/12/2004	07/13/2004	07/14/2004	
07/15/2004	07/16/2004	07/19/2004	07/20/2004	07/21/2004	

Appendix 3

Live Competition Results – April 2004

(http://www.cis.upenn.edu/~mkearns/projects/0507corrected.htm)

Days of test:

04/26/2004	05/03/2004
04/27/2004	05/04/2004
04/28/2004	05/05/2004
04/29/2004	05/06/2004
04/30/2004	05/07/2004

Trading agents were split into two groups: Red Pool and Blue Pool. Below are the final results over the two trading weeks.

RED POOL

Agent Name	Sharpe Ratio
ggc14	0.8334
hariharan	-0.1619
kenyon	1.1221
lkt	-0.4232
henis*	-12.6200

* This agent was a VWAP agent and evaluated differently

BLUE POOL

Agent Name	Sharpe Ratio
lo	0.7213
ramamoorthy	2.4963
sherstov	0.7559
subramanian	**0.5778**
wu	0.0432
henis*	-12.5931

* This agent was a VWAP agent and evaluated differently

The agent *subramanian* in the Blue Pool above is the GAA agent in the thesis.

References

[1] Neely C, Weller P and Dittmar R, *Is technical analysis in the foreign exchange market profitable? A genetic programming approach*, Journal of Financial Quantitative Analysis, Vol. 32, pp 405–26, 1997.

[2] Cohen J, Zinbarg E, Zeikel A, *Investment Analysis and Portfolio Management*, McGraw-Hill, 1986.

[3] Lewis C, *The Day Trader's Guide to Technical Analysis*, McGraw Hill, 2000.

[4] Murphy J J, *Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods & Applications*, PHI, 1999.

[5] Tradetrek Homepage: http://www.tradetrek.com

[6] Schwager J, *Technical Analysis*, Wiley 1996.

[7] Bauer R J, Dahlquist J R, *Technical Market Indicators: Analysis & Performance*, Wiley, 1998.

[8] Fang Y, Xu D, *The Predictability of Asset Returns: an approach combining technical analysis and time series forecasting*, International Journal of Forecasting, 2002.

[9] Kauffman P, *Trading Systems and Methods*, Wiley, 1998.

[10] Class Projects from CS395T: Agent Based E-Commerce at UT Austin (http://www.cs.utexas.edu/users/pstone/Courses/395Tfall03/resources/index.html)

(a) Ramamoorthy S, *A Strategy for Stock Trading based on Multiple Models and trading rules.*

(b) Sherstov A, *Automated Stock Trading in PLAT.*

(c) Subramanian H, *Automated PLAT Trading Agent using Order Imbalance in Volume.*

[11] Greenwald A, Jennings N R, Stone P, *Agents and Markets*, Guest Editor's Introduction, 18(6), Nov/Dec 2003

[12] Tino P, Schittenkopf C, Dorffner G, *Financial Volatility Trading using Recurrent Neural Networks*, IEEE Transactions on Neural Networks, 12(4), 2001.

[13] Wah B W, Qian M, *Constrained Formulations and Algorithms for Stock Predictions using Recurrent FIR Neural Networks*, AAAI/IAAI, 2002.

[14] Dunis C and Zhou B, *Nonlinear Modeling of High Frequency Financial Time Series*, Wiley 1998.

[15] Deboeck G (ed), *Trading on the Edge: Neural, Genetic and Fuzzy Systems for Chaotic Financial Markets*, Wiley, 1994.

[16] E. F. Fama, Random Walks in Stock Market Prices, Financial Analysts Journal, September/October 1965 (reprinted January-February 1995).

[17] Patrick S, *Trading Volume and Autocorrelation: Empirical Evidence from the Stockholm Stock Exchange*, Stockholm School of Economics, 1997.

[18] Malkiel B, *A Random Walk Down Wall Street*, WW.Norton, 1996.

[19] Kearns M, Ortiz L, *The Penn-Lehman Automated Trading project*, IEEE Intelligent Systems, 18(6), pp 22 – 31, Nov/Dec 2003.

[20] Hellstrom T, Holmstrom K, *Parameter Tuning in Trading Algorithms using ASTA*, Computational Finance, pages 343-357, Cambridge, MA, MIT Press, 1999.

[21] Dunis C et al., *Optimizing Intraday Trading Models with Genetic Algorithms*, Working Paper, Liverpool Business School, 1999.

[22] Island ECN: *http://www.island.com*

[23] Hennessey S, *Using an In-Class Simulation to teach Financial Markets*, Working Paper, University of Prince Edward Island, 1998.

[24] Fincoach.com Website: *http://fincoach.com*

[25] LeBaron B, *Building the Santa Fe Artificial Stock Market*, Working Paper, Brandeis University, 2002.

[26] Brock W, Lakonishok J, LeBaron B, *Simple technical trading rules and the stochastic properties of stock returns*, Journal of Finance, 47(5), pp, Dec 1992.

[27] Resistance & Support Reference: *http://www.stockcharts.com/education/ChartAnalysis/supportResistance.html*

[28] Refenes A P(ed.), *Neural Networks in Capital Markets*, Wiley 1995.

[29] Pictet O et al., *Real-time trading models for foreign exchange rates*, Neural Network World Volume 6**,** 713–44, 1992.

[30] Dempster M A H and Jones C M, *A real-time adaptive trading system using genetic programming*, Quantitative Finance Vol. 1, Institute of Physics Publishing, pp 397- 413, 2001.

[31] Mitchell M, *An Introduction to Genetic Algorithms,* MIT Press, 1996.

[32] Bauer R J, *Genetic Algorithms and Investment Strategies*, Wiley 1994.

[33] Stock Market Game website: *http://www.smgww.org*

[34] Virtual Stock Exchange website: *http://www.virtualstockexchange.com*

[35] Dempster M A H, Jones C M, *Can Technical Pattern Trading be Profitably Automated*, Working Paper, Judge Institutes of Management Studies, 1999.

[36] Li J, Tsang E P K, *Improving Technical Analysis Predictions: An Application of Genetic Programming*, Proceedings of Florida Artificial Intelligence Research Symposium, 1999.

[37] Oussaidene M, Chopard B, Pictet O V, Tomassini M, *Parallel Genetic Programming and its application to Trading Model Induction*, Parallel Computing, Vol 23, 1997.

[38] Sherstov A, Stone P, *Three Automated Stock Trading Agents: A Comparative Study*, AAMAS Workshop on Agent Mediated Electronic Commerce – VI, 2004.

[39] Gomes F, *Portfolio Choice and Trading Volume with Loss-Averse Investors*, London Business School, 2003.

[40] Allen F, Karjalainen R, Using *genetic algorithms to find technical trading rules*, J. Financial Economics, Vol.51, pp 245 – 271, 1999.

[41] Holland J H, *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Ann Arbor, 1975.

[42] Koza J R, *Genetic Programming: On the Programming of Computers by means of Natural Selection*, MIT Press, 1992.

[43] Papagelis A, Kalles D, *GA Tree: Genetically Evolved Decision Trees*, ICTAI, 2000.

[44] Dempster M A H, Payne T W, Romahi Y, Thompson G W P, *Computational Learning Techniques for Intraday FX Trading Using Popular Technical Indicators*, IEEE Transactions on Neural Networks, 12(4), 2001.

[45] Sharpe W F, *Mutual Fund Performance*, Journal of Business, January 1966.

[46] Pendersen C S, *Derivatives and Downside Risk.* Derivatives Use, Trading and Regulation, 2001.

[47] Littlestone N, Warmuth M K, *The Weighted Majority Algorithm*, University of California, Santa Cruz, 1992.

[48] Feng Y, Yu R, Stone P, *Two Stock Trading Agents: Market Making and Technical Analysis*, Dept. of Computer Sciences, UT Austin.

[49] Chordia T, Subrahmanyam A, *Order Imbalance and Individual Stock Returns*, Emory University, University of California, Los Angeles, 2002.

[50] PLAT website: *http://www.cis.upenn.edu/~mkearns/projects/pat.html*.

[51] Hariharan G, *News Mining Agent for Automated Stock Trading*, Thesis, University of Texas, Austin, 2004.

[52] Yahoo! Finance Website: *http://finance.yahoo.com/*

[53] Bollinger Bands Website: *http://www.bollingerbands.com/*

[54] Genetic Algorithm Pseudo code: *http://www.cs.bgu.ac.il/~sipper/ga.html*

Vita

Harish K Subramanian was born on April 3, 1981, the son of Lakshmi Subramanian and Ramamoorthy Subramanian. After completing his work at Choithram School, Indore, India, in 1998, he entered R.V. College of Engineering, Bangalore, India. He received the degree of Bachelor of Engineering in Instrumentation Technology from Visveswaraiah Technological University in July 2002. He entered The Graduate School at The University of Texas at Austin in August 2002.

Permanent address: A3/23 Gagan Apts, 2 Cross, Atmananda Colony,
Sultanpalya, Bangalore 560 032, India.

This thesis was typed by the author.