A Multi-agent Based Simulated Stock Market – Testing on Different Types of Stocks

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Abstract- In our previous work, we have developed a multi-agent based simulated stock market where artificial stock traders coevolve by means of individual and social learning and learn to trade stock profitably. We tested our model on a single stock (British Petroleum) from the LSE (London Stock Exchange) where our artificial agents demonstrated dynamic learning behaviours and strong learning abilities. In this paper, we extend our previous work by testing the model on different types of stocks from different sections of the stock market. The results from the experiments show that the artificial traders demonstrate stable and satisfactory learning abilities during the simulation regardless of the different types of stocks. The results from this paper lays the foundation for our future work – developing an effecient *portfolio manager* from a multi-agent based simulated stock market.

1 Introduction

In our previous work [1], we developed a multi-agent based simulated stock market within which artificial stock traders, modelled using artificial neural networks (ANNs), coevolve by means of individual learning and social learning, and learn to trade profitably. We tested the model on a single stock (British Petrolieum). Results from the simulation showed that the artitifical agents demonstrated dynamic behaviours and strong learning abilities. However, the fundamental principle of financial investments is diversification, where investors combine a variety of investments, such as stocks, bonds and real estate, to consturct efficient portfolios which bring the investors the greatest expected return under a given level of risk. Our aim is to introduce multiple stocks and other types of investments into the simulated stock market such that the artificial agents will be able to build up efficient portfolios. In other words we ultimately aim to develop an efficient *portfolio manager*. To achieve this, we are initially investigating how artificial traders will perform and behave with different type of stocks of different background, i.e. different fundamentals of the tested companies and different price patterns presented in their stock history. Will the artificial agents be able to learn to trade different types of stocks profitably regardless of their different background? Will the artificial agents behave differently under different market scenarios? These are the questions this paper aims to answer.

2 Background

In recent years, using multi-agent based models to study the stock market has become a promising research area due to the fact that this methodology reflects the nature of the stock market where heterogeneous investors with various expectations and different levels of rationality interact with each other through the market. See [2] for a good review of early work on agent based computational financial markets and [3] for the recent advances in evolutionary computation in economics and finance. Based on this methodology, various types of Artificial Stock Markets (ASM) have been developed [4,5,6]. These multi-agent based ASM models, rather than taking real data from real world markets, build the artificial stock markets from the ground up using a certain market structure together with the artificial stock traders modelled as heterogeneous adaptive agents. Inside these artificial stock markets, stock prices are generated endogenously and the resulting time series and market dynamics are studied [4,5,6].

Schulenberg and Ross [7,8] took another approach by introducing real market data into an adaptive agent based stock market model. They showed that their artificial agents, by displaying different and rich behaviours, are able to discover and refine novel and successful sets of market strategies that outperform a traditional buy-and-hold strategy and risk-less bond. In Schulenberg and Ross's model, artificial investors are modelled using Learning Classifier Systems (LCSs). One major problem with LCS systems is that the classifier rule conditions are designed explicitly before the evolutionary process of the LCSs begins, thus the novelty of evolved market strategies (LCSs) is questionable.

The other problem, both with Schulenberg and Ross's model and other early multi-agent based ASM models, is the ambiguity of the difference between individual learning and social learning within these models. Vriend [9] discussed the essential difference between individual and social learning, and its consequences for computational analysis using the experiments carried out in a standard Cournot oligopoly game. Vriend states that "*…the computational modelling choice made between individual and social learning algorithms should be made more carefully, since there may be significant implications for the outcomes generated.*" Chen and Yeh [6] embraced Vriend's research into their artificial stock market models and demonstrated that different learning mechanisms resulted in little difference in the macro-structures, i.e. the econometric properties of the time series of the generated artificial stock markets. However, different learning mechanisms generated different micro-structures of the resulting artificial stock markets regarding the traders' behaviour and belief.

Based on the study of Chen and Yeh [6] and Vriend [9], we have developed a multi-agent based simulated stock market where the basic market scenario, such as stock prices and trading volumes, are given extraneously. Inside the simulated stock market, artificial traders will coevolve by means of individual learning and social learning. Previously we tested the model on a single stock [1]. In this paper, we extend the testing of the model to another five stocks. From the results we observe the stable and satisfactory learning abilities of the artificial traders, and the importance of social learning relating to the adaptability of the agents.

3 The Model

3.1 Simulated Stock Market

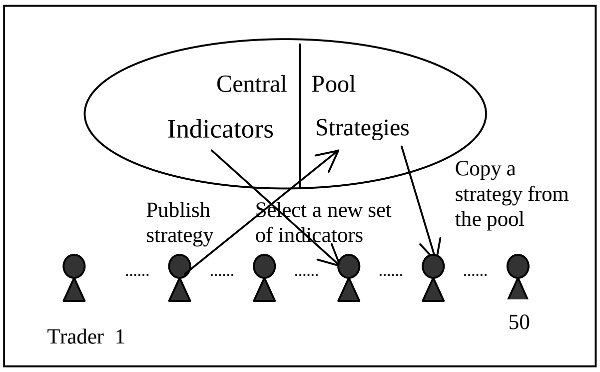

Figure 1: Multi-agent Based Simulated Stock Market

Figure 1 shows our multi-agent based model of a simulated stock market, which is described as follows:

1. Before trading starts, there are 50 active traders in the simulated stock market. There are 20 indicators and zero trading strategies in the central pool. The 20 available indicators are assigned an equal score of 1. Each trader selects a random number of indicators to use by using roulette wheel selection.
2. With the set of indicators selected, each trader generates ten different models. These ten models may have different network architectures, but they use the same set of indicators selected by the trader. The aim is for the trader to evolve better models from these ten by means of individual learning.
3. The time span of the experiment covers 3750 trading days, which is divided into 30 intervals. Each interval contains 125 days (6-month trading).
4. Each 125-day trading is sub-divided into intervals of 5 days. Each trader trades for 5 days, and then undertakes individual learning by means of a Genetic Algorithm (GA).
5. At the end of each 125-day trading, social learning occurs and each trader is given the opportunity to decide whether to look for more successful strategies from the pool or whether to publish his/her successful strategies into the central pool.
6. After social learning has finished, the system enters the next 125 trading days and steps 4, 5 and 6 are repeated.
7. For every transaction, buy means use all the cash in the trader's account and sell means sell all his holdings. Both margin account, where traders could buy stocks on credit, and short selling, where traders could sell stocks she/he does not hold, and buy it back at a later time, are not allowed. Traders are asked to pay a transaction fee of £10 for each transaction. Traders are also paid interest for any cash in their account, with an annual interest rate of 5%. Interest is calculated every half year.

3.2 Data and Data Pre-processing

Table 1 lists the profiles of the five selected stocks from the London Stock Exchange (LSE).

Table1. Five selected stocks on which the model is tested.

Company Name	Symbol	Sector
British Airways PLC	BAY.L	Transport
BT Group	BT.L	Telecommunications
Kingfisher	KGF.L	Retailers
Barclays	BARC.L	Banks
GLAXOSMITHKLINE	GSK.L	Pharmaceuticals

Besides the primitive historical share prices, other financial data is also used to compose 20 popular technical indicators that will be used by our artfcial stock traders as inputs to their neural networks. This data includes: trading volume; intra-day high, intra-day low; FTSE-100 index; DJ Oil&Gas Index(UK), S&P 500 Index and DJ INDU AVERAGE. All data was acquired from Yahoo Financial (http://uk.finance.yahoo.com/) and datastream financial service. Table 2 shows the 20 technical indicators available to the agents in the central pool.

Table 2. Technical indcators used as inputs into the neural networks. All values are normalised into the range of [0,1].

TI	Description
1	10 days moving average
2	20 days moving average
3	50 days moving average
4	200 days moving average
5	Closing price (normalized)
6	Rate of change (price)
7	Oscillator (price)
8	10 days bias
9	20 days volume rate of change
10	10 days relative strength
11	14 days relative strength
12	21 days relative strength
13	Stochastic oscillators (k%)
14	Fast stochastics (D%)
15	Slow stochastics (slow D)
16	FTSE-100 Index rate of change
17	Relative strength index to FTSE-100 Index
18	S&P 500 Index rate of change
19	DJ INDU AVERAGE index rate of change
20	DJ Oil&Gas Index (UK) rate of change

4. GA and Individual Learning

4.1 Prediction Model

The neural networks used by the traders are multi-layer feedforward networks. The networks are either 2-layer (no hidden layer) or 3-layer (one hidden layer). Two different types of activation function (sigmoid and tanh) are used. There is one single output node from the network. During the artificial agents' individual learning, the agents' prediction models will be evolved by means of a GA process. In order to facilitate the GA learning process, the description file of each neural network is designed in a way such that it can also be used as a chromosome within the GA, as shown in Figure 2. This is a concise representation of an artificial neural network in terms of evolutionary artificial neural networks (EANNs), see [10] and [11] for further discussion on the EANNs.

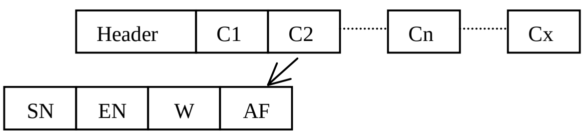

Figure 2: A neural network chromosome. Each chromosome consists of a header and a number of connections. The header contains general information about the network: starting input node, ending input node, starting hidden node, ending hidden node. Each connection, Cn, contains four components: starting node (SN), ending node (EN), weight (W), and activation function (AF). During the GA process, both the weights of the connection (W) and activation function (AF) are mutated.

Besides the mutation of weights and activation function, the structure of network is also evolved by means of adding a new node or deleting a node from the chromosome. SN and EN are used to keep track of the order of connections in the neural network.

As stated above, traders are allowed to use different sets of indicators for trading. Table 3 shows the different sets of indicators used by the 50 traders on the first trading day during the simulation of trading on the BAY.L share.

Table 3. Number of indicators (NOI) used by 50 traders on the frist trading during the simulation of trading on the BAY.L share.

Trader	NOI	Trader	NOI
1	11	26	18
2	3	27	3
3	15	28	14
4	4	29	18
5	16	30	17
6	15	31	2
7	7	32	5
8	2	33	3
9	14	34	1
10	16	35	17
11	1	36	13
12	11	37	7
13	15	38	16
14	15	39	6
15	16	40	1
16	2	41	11
17	3	42	11
18	19	43	9
19	8	44	19
20	13	45	16
21	1	46	13
22	13	47	8
23	11	48	4
24	12	49	14
25	4	50	4

4.2 Individual learning

Each of the five stocks will be traded in the simulated stock market for a period of 3750 trading days (usually starts from November 1987 and ends in January 2003). The 3750 trading days are divided into 30 intervals. Each interval contains 125 trading days. Individual learning occurs during every 125-day trading period. At the start of each period, each trader decides which set of indicators they will use to build their prediction models. Each trader builds ten models based on their selected indicators. These ten models all use the same set of indicators, but with different network architectures. Each trader evolves his ten models in an attempt to achieve better prediction models, using a GA described below.

On the first day of the 125-day trading period, a model is chosen, using roulette wheel selection, for the next 5 days trading. The selection is based on the ten models' scores. At the end of each 5-day trading, trader's ROP (rate of profit) is calculated using Formula 1.

$$ROP = \frac{W - W'}{W'} \times 10 \qquad (1)$$

W is the trader's current assets (cash + shares). W' is the trader's assets one week before. The selected model's score is then update using Formula 2.

$$m_i^n = m_i^n + ROP \qquad (2)$$

where i is trader i and n is the n^{th} model selected from the 10 models. Based on the new updated scores, four models are selected as parents, using roulette wheel selection. Another four models, those with the lowest scores, are selected and will be replaced by four new offspring (produced by the four parents through mutation). Overall, the four parent models selected and the two remaining models will stay intact and continue to the next generation together with the four new offspring. Model scores for the four new offspring are given by adding a small variance to its parent model's score, as shown in Formula 3 where *Var* is a random Gaussian number with a mean of zero and standard deviation of 0.1.

$$m_{offspring} = m_{parent} + Var \qquad (3)$$

As a trader's individual prediction models (neural networks) have a different numbers of hidden nodes, possibly a different numbers of hidden layers and maybe use different activation functions, it will not be sensible to use a crossover operator in the GA. Rather, the structure of the neural networks are evolved by having the probablilities to add or delete a node to its origin network without breaking down its origin network architechture. Evolving neural networks through mutation is also more feasible from its biological perspective. Therefore, within the GA we set the probability of crossover 0 and mutation to 1. The complete individual learning algorithm is given in Figure 3:

```
Select models to be mutated using
   roulette selection;
Select models to be eliminated;
Decide number of connections to be
   mutated, m;
i = 0;
While(i < m){
     Randomly select a connection;
     Weight = weight + Δw;
     i = i + 1;}
With 1/3 probability add hidden node;
With 1/3 probability delete hidden
  node;
replace models to be eliminated with
  the new mutated models;
```

Figure 3: Individual learning

The number of connections to be mutated, *m*, is a random integer between 0 and the total number of connections in the selected neural network. Δw is a random Gaussian number with a mean of zero and standard deviation of 0.1. Besides the mutation of weights, we also evolve the structure of the network by allowing the probability of adding or deletion of hidden nodes. After producing ten new models, the trader will select a model for the next 5 trading days, using roulette wheel selection. Individual learning occurs at the end of every 5-day trading for each trader.

5 Social Learning

After 25 weeks (125 days) of trading and individual learning, all traders enter a social learning stage. During social learning, all traders have the chance to see how other traders are performing. Traders may decide to learn from other traders, or publish their own successful trading strategies, as shown in Figure 1. At this stage, each trader will carry out a self-assessment. The trader's decision in social learning depends on the result from this self-assessment. Based on the methods used by Chen and Yeh [6], our trader's assessment is calculated using Formula 4, 5 and 6. First, the traders' rate of profit (ROP) (Formula 1) for the past six months is calculated, and the 50 traders are ranked from 0 to 49 according to their ROP.

$$S_{peer}^{i} = \frac{R_i}{49} \qquad (4)$$

R_i is the rank of trader i in the range of [0,49] (0 means highest rank with the greatest ROP). Formula 4 gives each trader a score in terms of peer pressure from other traders. In other words, this score shows trader *i*'s performance compared to other traders.

$$S_{self}^{i} = \frac{ROP - ROP'}{100} \qquad (5)$$

ROP is the rate of profit for the current six months trading. ROP' is the rate of profit for the previous six months. Formula 5 gives the trader's score in terms of his own performance in the past six months compared to the previous six months. Finally, these two types of performance are composed into Formula 6, which gives the overall assessment for trader *i*.

$$assessment_i = S_{peer}^{i} + \frac{1}{1 + e^{(1 - S_{self}^{i})}} \qquad (6)$$

The final assessments for 50 traders are then normalised into the range of [0,1]. Depending on their assessment, a trader may choose to:

1) If a trader's assessment is 1, and the trader is not using a strategy drawn from the pool, then publish the strategy into the central pool. Go into the next six months trading using the same strategy.

2) If a trader's assessment is 1, and the trader is using a strategy copied from the pool, do not publish it again, but update this strategy's score in the pool using their six month ROP. Go into the next six months trading using the same strategy.

3) If a trader's assessment is less than 0.9, the trader has 0.5 probability of copying a strategy from pool, which means the trader will discard whatever model he is using, and select a better trading strategy from the pool using roulette selection, and go into the next six months trading with this copied strategy. Or, with 0.5 probability, the trader will decide to discard whatever strategy he is using, and select another set of indicators as inputs, build 10 new models and go into next six months trading with these 10 new models.

4) If the assessment is between 0.9 and 1, the trader is satisfied with his performance in past six months and continues using that strategy.

A number of experiments with different threshold values were carried out to study the situation when a trader should be allowed to make public his strategy. We decided to choose 1 and 0.9 as the thresholds, because the general situation is that most of the traders are doing well, even when they are using different prediction models. Thus, only the really good traders can achieve an assessment of 1 after six months trading under unusual market conditions, with the majority of traders scoring between 1 and 0.9 and the badly performing traders scoring below 0.9.

Traders will also update scores of indicators they have used in the central pool based on their performance in the current six months using Formula 7 below.

$$I_i^n = I_i^n + ROP \qquad (7)$$

where *i* is the trader i. *n* is the n^{th} indicator used by trader i in the current six month trading. *ROP* is the rate of profit of the trader i in the current six months trading.

6 Experimental Results and Discussion

Our trading system is built on the basis of technical analysis theory where stock traders use various technical indicators from the stock market to act as buy and sell signals. The foundation of technical analysis theory in financial investments is the assumption that the stock price is predictable which is contradicatory to the Effecient Market Hypothsis (EMH) [12, 13]. The EMH says that, in its weak form, the price of an asset reflects all of the information that can be obtained from past prices of the asset, i.e. the movement of the price is unpredictable, because the EMH is based on the assumption that all news is promptly incorporated in prices; since news is unpredictable (by definition), stock prices are unpredictable. Here we are not interested in proving or disproving the EMH. We are interested in the trading strategies developed by the artificial agents during the simulation of trading on the basis of technical analysis theory. Figures 4 to 8 demonstrate the wealth growth lines of the 50 artificial traders during the simulations of trading on each five stocks. The results will be discussed in two different aspects: agents' performance and behaviours and the importance of social learning in a diversified environment with imperfect information, as shown in the following sections.

6.1 Artificial traders' performance and behaviours

There are two basic types of traders in the stock market. One is the 'fundamentalists' who are more interested in the background fundamentals of a company. This type of trader will buy shares of companies with good value and hold it for a certain period with the expectation of capital gain through the appreciation in the price of the stock. This is essentially the classic 'Buy and Hold' investment strategy. The other type of trader is the 'active trader', on which our artificial traders are modeled, who often ignore the fundamentals of a company. Active traders buy or sell shares based on the analysis of the share price graph of the stock, making use of various technical indicators to act as trading signals. In our previous experiment [1], we tested the simulated stock market model on a single stock (the British Petroleum) where the artificial active traders demonstrated strong learning abilities and dynamic learning behaviours. In this experiment the simulated stock model is tested on another five different types of stocks. The agents' performance is compared with the benchmark buy and hold strategy and a risk-free investment – bank savings as shown in figures 4 to 8.

Figures 4 to 8, except for the buy and hold line and the bank savings line, show the performance of the 50 artificial agents in each simulation respectively. From the buy and hold lines which essentially indicate the historical price movement of the particular share, we can see each of the five stocks, ignoring their different background fundamentals, demonstrates different price patterns. In order to observe the evolution of the artificial traders more clearly, we use the result from the simulation run on the BT share and select six typical traders to illustrate the adaptive learning of the agents and the different types of traders and trading strategies developed, as depicted in figure 9. From figure 9, trader 29, 22 and 30 can be described as 'aggressive traders' who followed the trend of the stock price closely and accumulated their wealth in frequent trading. These type of strategies worked well during the upturn of the market, however, during the downturn of the market, the adaptability of the agents become essential to the success of the trader. While trader

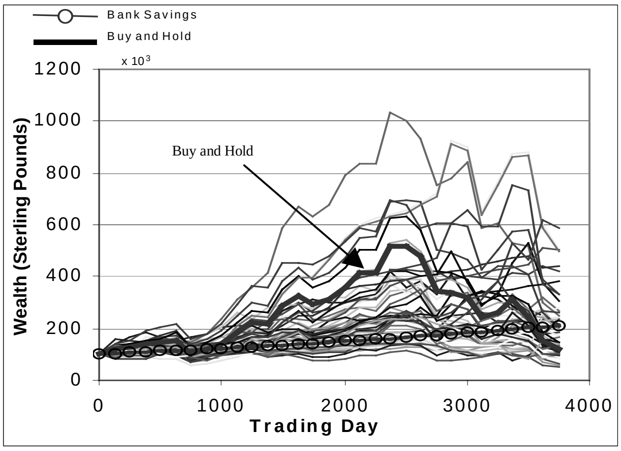

Figure 4: Simulation of Trading on BAY.L

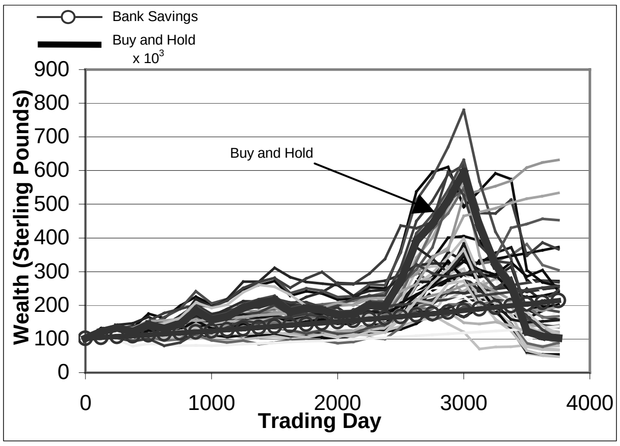

Figure 5: Simulation of Trading on BT.L

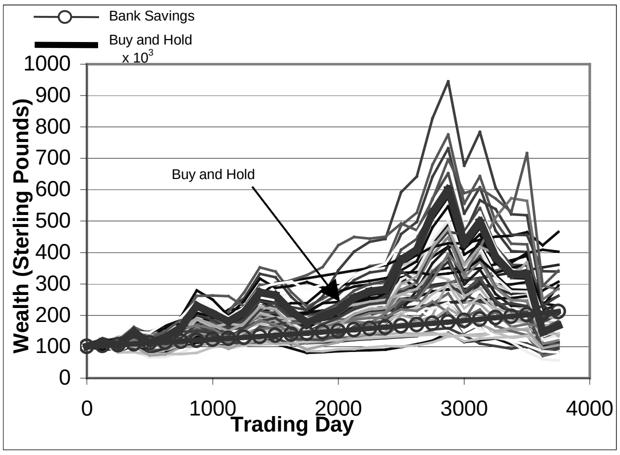

Figure 6: Simulation of Trading on KGF.L

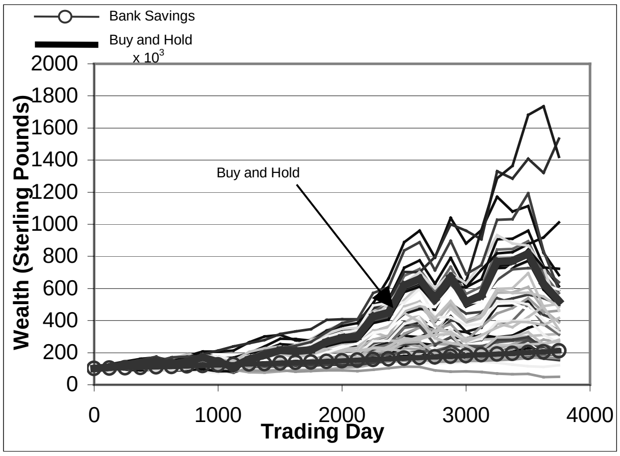

Figure 7: Simulation of Trading on BARC.L

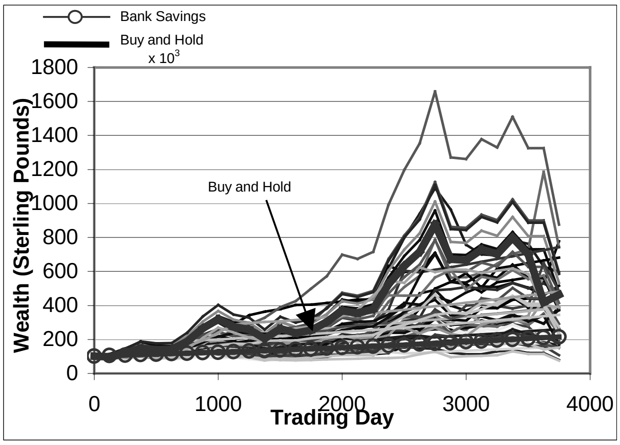

Figure 8: Simulation of Trading on GSK.L

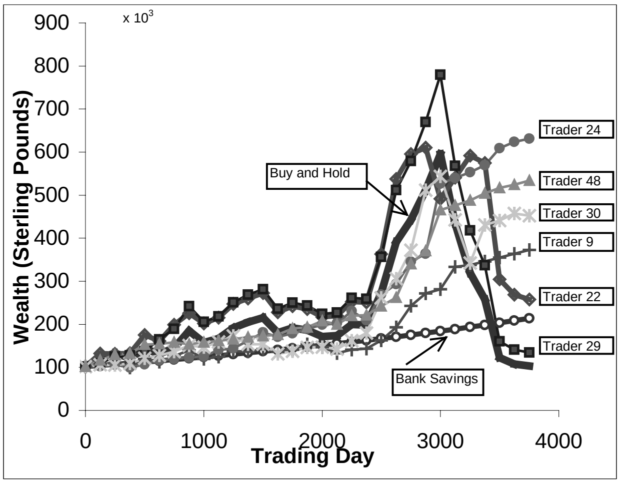

Figure 9: Different types of traders and trading strategies developed during the simulation of trading on BT share

Table 4. Artificial agents' performance compared with benchmarks, buy and hold strategy and bank savings

Description	BAY.L	BT.L	KGF.L	GSK.L	BARC.L
Outperform Buy & Hold (out of 50 traders)	36	36	28	15 (30%)	11 (22%)
Outperform Bank Savings (out of 50 traders)	18 (36%)	16 (32%)	18 (36%)	33	35
Cumulative Total Return (Buy & Hold)	18.26%	0.97%	65.03%	351.26%	417.97%
Cumulative Total Return (Bank Savings)	109.76%	109.76%	109.76%	109.76%	109.76%
Maximum Cumulative Total Return (Best Trader)	482.86%	519.63%	359.85%	753.53%	1424%

29 failed to adapt to the changed market, trader 22 and 30 managed to adapt their strategy to the changing market and ultimately beat the bank savings. On the other hand, trader 24, 48 and 9 can be described as 'conservative traders' who are usually more cautious about the market. These traders had less frequency in trading compared to the aggressive traders, thus usually having lower growth lines than the agressive traders during the upturn of the market. However, once the market changed to downturn, these conservative traders usually adapted themselves to the new environment much faster, and transferred their assets from the stock market back to the less risky banks. We can see during the simulation, the traders are evolving, their trading strategies are also evolving and adapting to the new environment. We observed that the adaptability of the agents is essential in a volatile environment like the stock market, rather than just good timing of trading. Referring to figures 4 to 8, we observed similiar evolutionary process of the traders in each of the simulations: different types of traders and different type of good trading strategies were developed, regardless of the different background of the tested stocks. In the cases of BAY.L, BT.L, and KGF.L share, where the stock prices basically follow a pattern of an upturn followed by a sharp downturn, bank savings will perform well. On the contrary, in the cases of BARC.L and GSK.l share, buy and hold strategy performs well. Thus, we compared the performance of the artificial agents with bank saving for BAY.L, BT.L and KGF.L share, and with buy and hold strategy for GSK.L and BARC.L share in table 4. Table 4 shows, during the five simulation, 22% to 36% of the artificial traders were able to learn to develop good trading strategies that beat the market. Table 4 also shows the performance of the best trader from each simulation in the comparison of the benchmark buy and hold strategy and the risk-free bank saving.

In summary, the simulation run on the five different types of stocks shows that the artificial agents in our simulated stock market model demonstrate stable and satisfactory learning abilities regardless of the different background of the traded stocks, but diversified learning behaviours related to the different stock price patterns. This provides us with a good foundation for our future work: building effecient portfolio managers in the simulated stock market model.

6.2 Social Learning in A Diversified Environment

If we view the simulated stock market as a space of trading strategies, the evolutionary process of the simulation is essentially the process of artificial agents searching for the optimal trading strategies under certian market scenarios. Within this search space, there are different regions where each region represents trading strategies using the same set of information from the environment. Whether the agents are able to escape from one region and jump into another region to search for better solutions becomes critial in terms of the quality of the whole population of agents and the adaptability of the agents in a diversified environment where different sets of information could be perceived, such as the stock market.

Referring to Schulenburg and Ross's model [7,8], three different types of traders were evolved in seperate GA processes, which are essentially three seperate individual learning processes. Each of these three types of traders uses a certain set of informations from the market for decision making. Each type of trader is constrained to that particular set of information during the evolution. There are few questions we could ask here. How those types of traders are defined? Are they defined based on the researchers' experience or pratically from the market? Why used these three particular sets of information, not other sets of information? How many different sets of information can be defined from the stock market, or a diversified environment? How do we define which set of information is a good combination, and which are not important? These are the questions that should be answered by a social learning process where different agents use different set of information from the environment. In another sense, Schulenburg and Ross's model is still a single learning process in a particular region; it did not solve the problem of learning across different regions in the global space. This is also another major reason we questioned the novelty of the strategies developed in Schulenburg and Ross's model.

Traditional methods for neural network learning using evolutionary algorithms are also restricted to a fixed set of inputs, such that the evolutionary process is essentially the evoultion of the neural network architecture only. The learning of agents is actually trapped in a local optimal of a region. This type of learning with a pre-defined set of information does not solve the fundamental problem in an diversified environment: what information a person can possibly have and what information to use.

The social learning mechanism implemented inside our simulated stock market model acts as the bridge through which the agents escape from a local region and search in the global space for the optimal strategy. We believe that the social learning plays an important role in terms of quality of the whole evolutionary population and the adaptability of the learning agents in a diversified and volatile environment.

More generally, social learning plays an important role in any decision-making environment which are diversified and with imperfect information. The most obvious example is the society for human beings, or any living creatures. Another example is the imperfect games, such as poker, where each player perceives different set of imperfect information from the game and makes a decision.

7 Future Work

In the future work, we will introduce various types of investments and portfolio management theory into the simulated stock market model with the aim to build effecient portfolio managers. We will also look at how social learning affects the learning and adaptability of the agents in a diversified and imperfect environment by changing the frequency and percentage of social learning during the simulation.

Achnowledgement

Many of the reviewers' recommendations have been incorporated into this paper. We also plan to use some of the comments we received in our future work. We would like to thank all the reviews for their excellent comments and helpful advice, which improves not only the paper but also our future work.

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