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Emergent Mutualisms in an Agent Based Economic Simulation

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Abstract

This report defines a model for an agent based economic simulation. The simulation is then tested with different parameters before moving on to observing emergent mutualisms raised from bartering and specialisation.

Contents

List of Figures

Chapter 1

Introduction

1.1 Objectives

The aim of this project is to implement an agent based economic simulation that is capable of evolving the division of labour and trade.

If agents are able to specialise in the production of a commodity, this allows for a surplus production by an individual agent. Creating a surplus of a certain commodity allows for other agents to also specialise. This process causes economic growth which can be defined as a disequilibrium[5].

1.2 Background and History

"Virtually all civilizations, except the Incas, developed some form of money. Today our currencies and banking systems increasingly extend beyond national boundaries. However, co-existing with that movement there has been a revival of interest in alternative financial systems" [2].

Adam Smith's Wealth of Nations describes how the driving force behind economic growth is the division of labour and that this is only limited by the extent of the market. However Allyn Young (1928) claims that the division of labour is limited by the division of labour [5].

It has been a common conception in social science that an agent based economic simulation at a micro-scale will fail because human economies contain far too much complexity at the micro-scale (agent level), and this complexity is essential. On the other hand certain phenomenon that can be seen to emerge in simple simulations that are based on basic human needs and desires from the macro-scale[4].

In studies it has been seen that artificial learning agents can be made to replicate complex human behaviour[1]. Arthur argues that there are limits to human rational, but questions what these limits are.

Simple rules often give rise to complex behaviour[13]. By building an agent-based model of bartering that is as simple as possible (but no simpler) we hope to shed light on the origins of economic complexity at the macro-scale.

1.3 Similar Projects

There are a number of agent based economic simulations [3, 7, 8, 9, 10, 11, 12]. Here I briefly outline two of them.

1.3.1 The MUD Simulation

The simulation described by Grimm and Mitlohner [11] is a virtual world in which agents can explore rooms, take and drop items and also use these items for purposes such as eating or wearing. The agents in this simulation can be either computer based or human based. Both human and computer agents are capable of the same actions. This simulation is implemented using an Internet text based MUD (multi user domain), commonly used for online adventure games.

They set out to create a simulation that did not rely on complex rules. These rules are dynamic and hard to define. In order to achieve this they modelled the economic behaviour of individual agents and expected to see these complex rules arise from the agents interacting with each other.

Grimm and Mitlohner state that

> "we provide the following commands as the minimum necessary for simple economic transactions."

The economic features that this MUD simulation provides are:

1. Starting a deal.
2. Negotiations.
3. Standardized communication.

If an agent owns an item that can be sold, they may initiate a deal. This creates a contract, which contains information about the parties concerned and their roles (who is selling and who is buying), the object up for sale and any additional information, such as price, date of delivery or quantity.

After this contract is created the agents can negotiate the terms. This is done through an *offer* command. Once an offer has been issued to an agent, they may respond by issuing another offer back, accepting the deal or withdrawing from the deal. Agents can place as many offers as they like during this process, until one of the agents accepts or withdraws from the deal. There is no cost for this process, apart for the time required to process the information.

Once an agent accepts the deal the system checks that it is valid. A deal may not be valid if an agent does not have enough money for payment or enough of the goods to be sold. In which case the partner agent is informed of this and updates his rating of the other. This requires the agents to map out and remember other agents ratings within the same virtual world.

In order for the agents to communicate with each other, this MUD implements a simple messaging service. These messages consist of three main parts: an address, message type and one or more triples of object/property/value. The messages are checked against the agent that sent them. If the agents produce non-confirming messages, the MUD drops the messages.

The MUD simulation tries to implement an agent based economic simulation in the simplest way possible. However it has been modelled so that humans can directly act as agents. Because of this the computer based agents are geared towards competing with human base agents. This is evident as the agents map out other agents in its world based on the results from deals.

Due to this mapping the agents have prior knowledge of an agent when initiating a deal (unless they have never dealt with the particular agent before). To successfully trade with another agent, an agent must build up enough knowledge about the other agent. This may take more than a single bartering session with any single other agent.

1.3.2 OPTIMAES

The simulation described by the OPTIMAES (Open Project to Investigate Money and Economic Systems)[8] group is one that purely contains agents in a network that trade commodities. It also looks at several different network configurations.

The agents in this simulation have several attributes: the capacity to create each amount of resource, a consumption rate for each resource, a minimal need for each resource and a current store for each resource. At each step in the simulation each agent receives an amount of each resource, depending on its capacity to create, the agent then consumes an amount of each resource also. Therefore an agent that can not create more than it can consume will die when its resources run out.

Agents are located in social networks. That is, each is connected to a subset of the other agents in the network. In each step in the simulation, after the agents have created and consumed their resources, they get an opportunity to interact with their connected agents. The agents can interact by giving gifts, bartering for a lose or bartering for a profit.

The social networks can be configured in different ways. These include: local connected, randomly connected and fully connected. In the future, the OPTIMAES team wants to look at other more complex networks. Such as a network that rewires itself based on economic activity.

1.4 Outline

In chapter 2 we define the model for our agent based barter simulation. In chapter 3 we investigate different barter strategies. In chapter 4 we investigate specialisation and in chapter 5 we summarise.

Chapter 2

Modelling the Barter Process

2.1 Agents

An agent is an entity that barters and trades within the simulation. Each agent holds a certain amount of each commodity. This amount is determined by the effort the agent puts into producing the commodity. All the agents in the simulation are bound to use a fixed, common total amount of effort to produce commodities. However they can choose how this effort is distributed among the commodities.

For ease of explanation:

1. Units of effort are measured in ”days”.
2. The agents have 2 days to produce all of their commodities.
3. There are two different types of commodities in the world (apples and oranges).

In this case agents can put anywhere from 0 to 2 days of effort into producing apples and then the rest of their effort, if there is any remaining, into producing oranges.

The agents can be seen as a form of a Mobile Automata [13].

2.2 Utility and Productivity

2.2.1 Utility

The utility function u quantifies how much a certain combination of commodities C is worth to a particular agent. For simplicity, we will assume all agents use the same utility function.

For example, if you were going to be stranded on a deserted island and had three choices of what you are allowed take with you:

Option	Food (units)	Water (units)	Total (units)
A	198	2	200
B	2	198	200
C	40	40	80

You would choose option C, as the other two options would leave you with almost no water or almost no food. Both of which, you are not going to last long on, even though you would have more than twice as much to consume. Therefore a linear function that just sums the commodity units would not reflect reality.

From the simple example above we can see that we need at least a logarithmic function such as:

$$u(C) = \log(C_1) + \log(C_2) + ... + \log(C_n)$$

Where C is a list of commodities and C_n is the nth commodity in the list.

We can see from the table below that option C is a better choice than option A and B. As this reflects the fact that both food and water must be present in modest amounts.

Option	Food (units)	Water (units)	Utility
A	198	2	2.598
B	2	198	2.598
C	40	40	3.204

2.2.2 Productivity

The productivity function p determines how much of a certain commodity an agent will receive if they put in an T amount of effort to produce it.

For example, suppose there are two agents, A_1 and A_2 that have 2 days to produce all their commodities, of which there are two different types, apples and oranges. Agent A_1 decides to put all its effort into producing apples, while agent A_2 decides to put an even amount of effort into producing apples and oranges. The agents efforts will look like this:

Agent	Effort (Apples)	Effort (Oranges)
A_1	2	0
A_2	1	1

As agent A_1 has put its complete effort into producing apples, it has in effect specialised. Because agent A_1 is specialised in creating apples it has become more efficient at producing them. Agent A_2 has put only half the amount of effort into creating apples as agent A_1, therefore agent A_2 is not as good at producing apples as agent A_2. However agent A_2 will have some oranges and agent A_1 will not.

From this problem we can see that more than just a plain linear function is required to reflect the reality that specialisation has benefits. This is because if we have agent A_1 and an agent A_2 where agent A_1 puts in T_1 amount of effort and agent A_2 puts in T_2 amount of effort and $(T_1 > T_2)$, then if both agents A_1 and A_2 increase their effort by G, we want to see $\Delta p(T_1) > \Delta p(T_2)$, where p is the productivity function.

From the simple example above we can see that we need at least an exponential function such as:

$$p(T) = e^T$$

Using the example above, this equates to:

Agent	Stock (Apples)	Stock (Oranges)
A_1	7.389	1
A_2	2.718	2.718

As we can see from this table that even though agent A_1 put 0 effort into producing oranges, it still got 1 unit of oranges. This is implausible in many situations and therefore the function needs to be adjusted so that a 0 effort does not result in a positive outcome. Since if this were true then the agents would be able to get something from nothing.

In addition, if we look at figure 2.1, we can see that the agents utility function is linear.

$$T = u(p(T_1)) + u(p(T_2)) + ... + u(p(T_n))$$

This means that the two function are an inverse of each other. This is undesired as one function reverses the other and creates a flat utility rate. See figure 2.1 for illustration.

Therefore we need a new productivity function. The function below will not produce a flat utility rate and putting 0 effort into producing a commodity will not result in a positive outcome. See figure 2.2 for illustration.

$$p(T) = e^T - 1$$

Using the example above, this equates to:

Agent	Stock (Apples)	Stock (Oranges)	Utility
A_1	6.389	0.000	-6.20
A_2	1.718	1.718	0.47

Without trade, specialisation is not desired, as in the table above, agent A_1 has not oranges. Even though it has a lot of apples, which gives it 0.804 utility, this is cancelled out by the lack of oranges, which takes 7.00 (0 is substituted for a very small number) utility. Giving the total of -6.20 utility.

With trade, agent A_1 would be able to swap commodities with agent A_2 and make a profit. This is because agent A_1 is desperate for oranges and will pay a lot of apples for not not many oranges. Therefore specialisation is profitable.

2.3 Simulating Bartering

2.3.1 Offers

Agents communicate with other agents through ”offers”. An offer represents a potential trade opportunity. This can be seen as a contract between two agents, where the agents adjust the terms until both parties are satisfied. See figure 2.3.

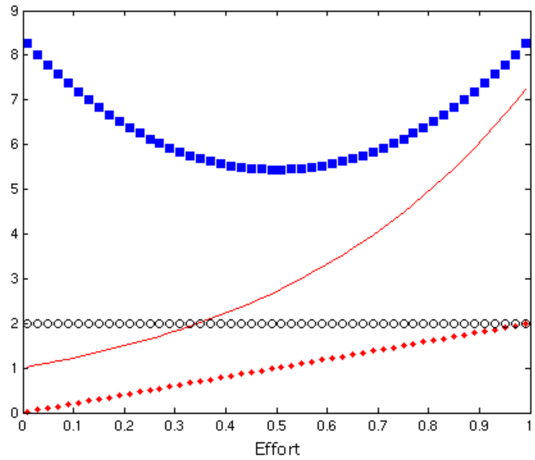

Figure 2.1: Original utility and productivity function of 2 commodities. (Red line represents productivity of commodity 1, red dots represent the utility from just the productivity of commodity 1, blue squares represent total productivity and circles represent the agent's utility)

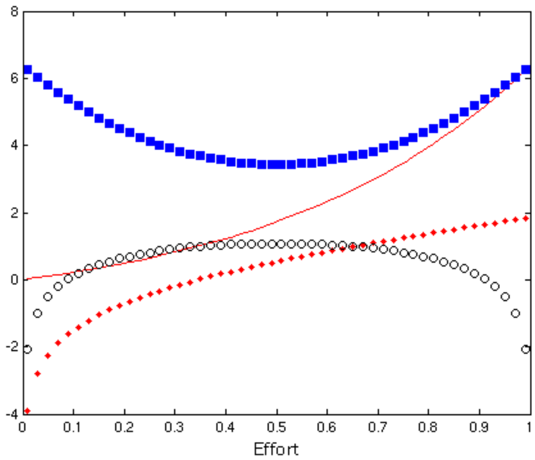

Figure 2.2: Revised utility and productivity function of 2 commodities. (Red line represents productivity of commodity 1, red dots represent the utility from just the productivity of commodity 1, blue squares represent total productivity and circles represent the agent's utility)

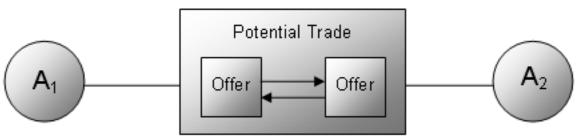

Figure 2.3: Network graph of two agents and their offers.

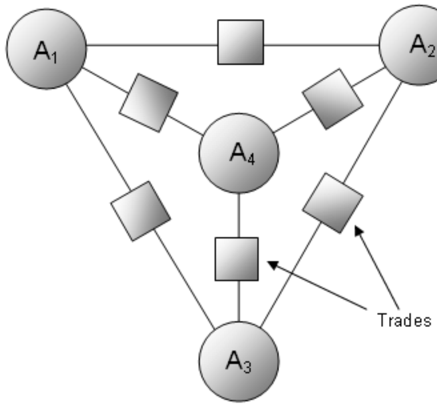

Figure 2.4: Network graph of multiple agents and their offers. Here there are 4 agents and each can trade with any of the others. Clearly other graphs are possible, such as chains, trees and rings.

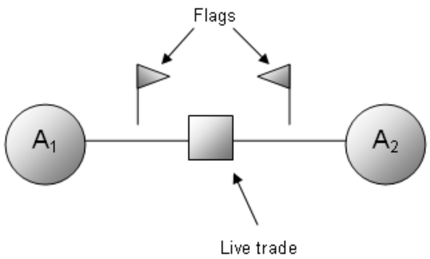

Figure 2.5: Network graph of 2 agents. Both agents are interested in each others offers therefore both their flags are set and the offers become a live trade.

An offer consists of a single commodity type and an amount (ie. 2 apples). There is only one offer per pair of agents. Each agent assesses each offer that is available to them by finding out if the potential trade will increase the worth of their stock pile. This worth is quantified by the *utility* function.

Each agent has access to an offer from each other agent that it is connected to. Or in other words the agents are fully connected through offers.

2.3.2 Flags

A flag denotes whether the agent is interested in a particular trade from another agent. An agent is interested in an trade if the agent stands to make a utility gain from it in its current state. If it is interested then the flag on the offer of the trade is set. If both agents set their flags on a trade, it then becomes a ”live trade”. Flags are used by agents to help make bartering decisions.

When an agent has the chance to barter, it first must check and set its flags. Each agent has a flag associated with each other agent. An agent sets this flag if its stock pile amount plus the trade amount is an increase to the agent's utility.

The agent's utility gain G is defined as:

$$G = u(S + P) - u(S)$$

Where S is the current stock and P is the change in the stock due to the potential trade. An agent sets a flag on an offer if $G > 0$. For example:

Offer	G	Flag
A	0.5	set
B	-0.1	
C	1.2	set
D	-1.4	

After a set number of turns in which both agents have their flag set on an offer, the offers turns into a trade and the agents exchange commodities as specified by the trade. Once this trade is complete, the agent's new utility will now be equal to the agent's old utility plus the utility gain specified in the table below.

2.3.3 Choosing a Commodity to Trade

When choosing a commodity to trade, agents initially choose the commodity that they have the most of. This is because the commodity that they have the most of is worth the least to them. This is due to the utility function. This is the simplest way to choose a commodity, except for choosing one at random.

However, it is not always the best strategy for an agent to barter with the commodity they have the most of. It depends on the other agents in the simulation, if none of the other agents in the simulation desire a certain commodity then an agent is stuck trying to trade a commodity no agent wants.

This can be avoided by timing how long it has been since the agent's last trade. If the time period is long enough then the agent switches to another commodity and tries again. This can spawn a chain reaction of trades between other agents as even a single trade can change the desires of the rest of the population.

2.3.4 Simple Barter Strategy

The first revision of the simulation is designed as a proving ground for the basic rules that have been defined. In this simulation agents start with random commodities and are allowed to barter and carry out trades.

The running time of the simulation is up to the agents. The simulation will not end until all the agents have stopped trading for a set number of turns. It is crucial that this value is high enough as even a very small trade between two agents can spawn many other trades between other agents. This is because a trade between two agents alters their need for different commodities. Other agents may now have an offer that is profitable to the agent that was not before.

An agents best live trade is one that both agents are interested in, or from the point of view of the agents, they both have their flags set on it. This means that both agents will profit from the trade in its current state. If the agent has more than one live trade, then the best live trade is the one that will produce the highest utility gain for that agent.

This simulation will use sensible barter strategy that we will predefine and does not evolve or change in any way. This strategy is defined in the table below. This table refers to what an agent does when evaluating and responding to a specific offer.

The third column, $G - G_{best}$, refers to the difference between the trade under consideration and the best live trade (or zero if there are no live trades). This has been simplified in this table to being either -ve (negative) or +ve (positive), this allows the agent to weigh up the current trade in relation to the agents best live trade.

If x is how much of the currently selected commodity the agent is offering in return. Then last column, Δx, refers to how much the agent will alter x in response to the other agents offer under consideration.

Class	Partners Flag	$G - G_{best}$	Δ x
I_1	not set	+ve	down
I_2		-ve	?
I_3	set	-ve	up
I_4		0	?

This table classifies an offer into one of the four categories. This aids the agents in making their bartering decisions. The class of offers can be described as follows:

I_1 The first class of offer is when an agent's offer is too expensive (the partner agent's flag is not set) and the agent stands to make more from this offer than from its best true offer.

I_2 The second class of offer is when an agent's offer is below its bets true offer, but the partner agent is still not interested.

I_3 The third class of offer is when an offer is below an agent's best true offer and the partner agent is interested in the offer.

I_4 The fourth class of offer is when the offer is the agent's best true offer.

The simple barter strategy is the response to the different types of the above classes of offers. These responses can be described as:

I_1 If an agent's offer is too expensive, then we need to increase what we are offering to interest them.

I_2 In this case we can either raise or lower our offer, but too keep the strategy simple we will leave the offer as it is.

I_3 This is effectively a backup offer, but it may surpass our best true offer, therefore we should decrease what we are offering a little bit and see how cheap we can get it.

I_4 If this is out best true offer then we should leave it as it is or risk loosing it.

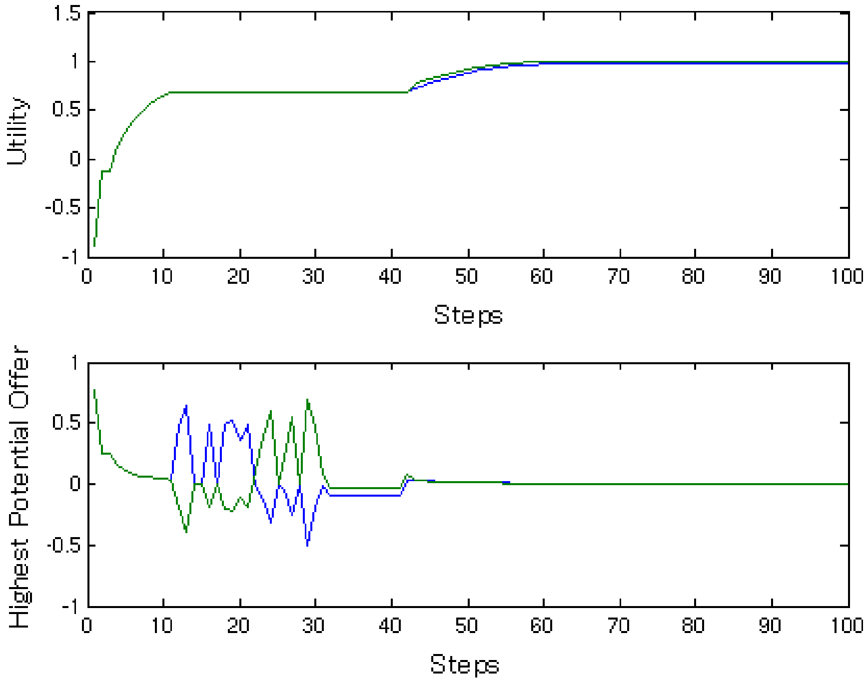

Figure 2.6: 2 agents, 2 commodities bartering

Taking these classes and responses into consideration the following strategy can be seen as sensible:

Class	Δ x
I_1	+0.1
I_2	0
I_3	-0.01
I_4	0

2.3.5 Two Agent Network with two Commodities

This is the simplest setup for the simulation. With this simple simulation we can see if the agents are able to barter and trade sensibly.

The agents start with set commodities. Each of the two agents will be fully specialised in a commodity type. This will allow the agents to try and gain the highest possible utility through bartering without having to deal with an unequal spread of commodities. See the table below for details.

Agent	T_1	T_2	C_1	C_2	U
A_1	1.98	0.02	6.243	0.020	-0.900
A_2	0.02	1.98	0.020	6.243	-0.900

The simulation is run and there are 31 trades. Effectively agent 1 trades 3.1 units of commodity 1 for 3.1 units of commodity 2 with agent 2. The resulting commodities and utilities look like this:

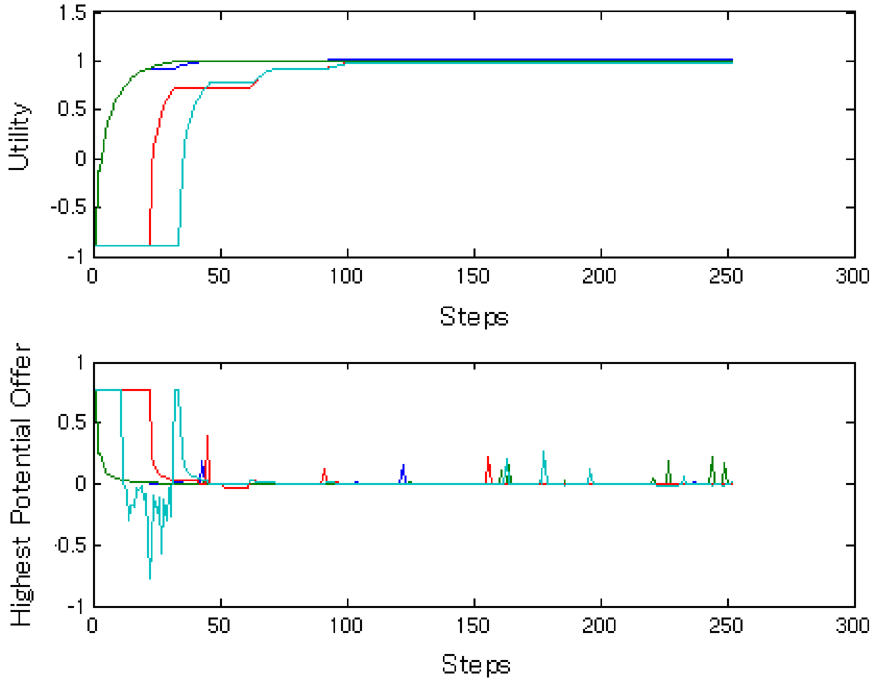

Figure 2.7: 4 agents, 2 commodities bartering

Agent	C_1	C_2	U
A_1	3.043	3.120	0.977
A_2	3.220	3.143	1.005

Figure 2.6 shows the agents utility as the simulation progresses.

The simple barter strategy works as expected for 2 agents and 2 commodities. The agents start almost completely specialised and barter and trade until there is an equilibrium between the agents and their commodities.

When an agent's efforts of its different commodities are all roughly at the same level, I will call this an equilibrium state and use it to describe the state of an agent's efforts from now on. An agent in the equilibrium state is the opposite of an agent being in a specialised state.

2.3.6 Multiple Neighbour Network

This is the next step, multiple neighbours and 2 commodities. For this experiment we will use 4 agents. Apart from the number of agents the setup for this experiment will be the same as the setup for the previous 2 agent, 2 commodity experiment.

This is the agent setup at the beginning of the simulation:

Agent	T_1	T_2	C_1	C_2	U
A_1	1.98	0.02	6.243	0.020	-0.900
A_2	0.02	0.98	0.020	6.243	-0.900
A_3	1.98	0.02	6.243	0.020	-0.900
A_4	0.02	1.98	0.020	6.243	-0.900

The simulation is run and there are many trades. Figure 2.7 shows the progression of the agents and their utilities through out the simulation. The summary or trades is as follows:

```
Agent 1 received 0.35 of commodity 1 from agent 3
Agent 1 gave 2.1 of commodity 1 to agent 2
Agent 1 gave 1.3 of commodity 1 to agent 4
Agent 1 received 2.1 of commodity 2 from agent 2
Agent 1 received 1.4 of commodity 2 from agent 4
Agent 1 gave 0.3 of commodity 2 to agent 3

Agent 2 received 2.1 of commodity 1 from agent 1
Agent 2 received 1.1 of commodity 1 from agent 3
Agent 2 received 0.1 of commodity 2 from agent 4
Agent 2 gave 0.09 of commodity 1 to agent 4
Agent 2 gave 2.1 of commodity 2 to agent 1
Agent 2 gave 1.1 of commodity 2 to agent 3

Agent 3 gave 0.35 of commodity 1 to agent 1
Agent 3 gave 1.1 of commodity 1 to agent 2
Agent 3 gave 1.7 of commodity 1 to agent 4
Agent 3 received 0.3 of commodity 2 from agent 1
Agent 3 received 1.1 of commodity 2 from agent 2
Agent 3 received 1.7 of commodity 2 from agent 4

Agent 4 received 1.3 of commodity 1 from agent 1
Agent 4 received 0.09 of commodity 1 from agent 2
Agent 4 received 1.7 of commodity 1 from agent 3
Agent 4 gave 1.4 of commodity 2 to agent 1
Agent 4 gave 0.1 of commodity 2 to agent 2
Agent 4 gave 1.7 of commodity 2 to agent 3
```

The resulting commodities and utilities look as follows:

Agent	C_1	C_2	U
A_1	3.193	3.220	1.012
A_2	3.130	3.143	0.993
A_3	3.093	3.120	0.985
A_4	3.110	3.042	0.976

The simulation with the given rules handles multiple agents without any trouble and behaves as expected.

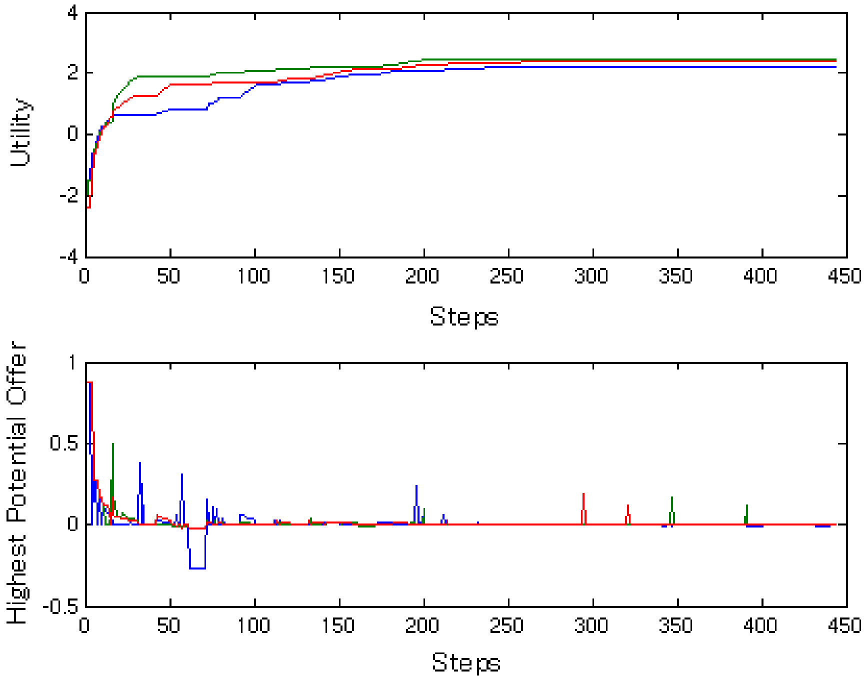

Figure 2.8: 3 agents, 3 commodities bartering

2.3.7 Multiple Neighbour Network with multiple Commodities

The next step in testing the rules is to add in more than 2 commodities. To keep the simulation simple we will drop the number of agents down to 3 and add another commodity to make 3 also. Therefore we will have 3 agents and 3 commodities.

This is the agent setup at the beginning of the simulation:

Agent	T_1	T_2	T_3	C_1	C_2	C_3	U
A_1	2.97	0.015	0.015	18.492	0.015	0.015	-2.374
A_2	0.015	2.97	0.015	0.015	18.492	0.015	-2.374
A_3	0.015	0.015	2.97	0.015	0.015	18.492	-2.374

The simulation is run and there are many trades. Figure 2.8 shows the progression of the agents and their utilities through out the simulation. The summary or trades is as follows:

```
Agent 1 gave 7.465 of commodity 1 to agent 2
Agent 1 gave 5.550 of commodity 1 to agent 3
Agent 1 received 5.950 of commodity 2 from agent 2
Agent 1 gave 0.520 of commodity 2 to agent 3
Agent 1 gave 0.934 of commodity 3 to agent 2
Agent 1 received 6.440000 of commodity 3 from agent 3

Agent 2 received 7.465 of commodity 1 from agent 1
Agent 2 gave 0.750 of commodity 1 to agent 3
Agent 2 gave 5.950 of commodity 2 to agent 1
```

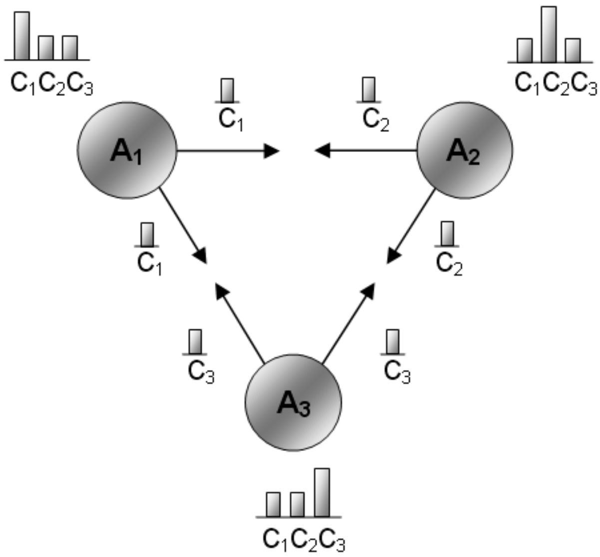

Figure 2.9: Flow of commodities in multi-neighbour, multi-commodity specialised simulation

```
Agent 2 gave 5.770 of commodity 2 to agent 3
Agent 2 received 0.934 of commodity 3 from agent 1
Agent 2 received 5.790 of commodity 3 from agent 3

Agent 3 received 5.550 of commodity 1 from agent 1
Agent 3 received 0.750 of commodity 1 from agent 2
Agent 3 received 0.520 of commodity 2 from agent 1
Agent 3 received 5.770 of commodity 2 from agent 2
Agent 3 gave 6.440 of commodity 3 to agent 1
Agent 3 gave 5.790 of commodity 3 to agent 2
```

The resulting commodities and utilities look as follows:

Agent	C_1	C_2	C_3	U
A_1	5.477	5.445	5.521	2.217
A_2	6.730	6.772	6.739	2.487
A_3	6.315	6.305	6.262	2.397

2.4 Interesting Points

2.4.1 Commodity Choice

During the course of a simulation the best commodity for an agent to trade with is not always the commodity that the agent has the most of. This happens when two agents manage to accumulate a lot of the same commodity and they both try to trade it at the same time. The two agents reach a dead lock.

This can be avoided if an agents tries other commodities if the agent has not made a trade in a sensible amount of time. This can be seen in figure 2.4. The agents become dead locked at step 49. One of the agents gives up on a commodity and switch to another one at step 52. As you can see in the graph, this spawns many more trades and the agents increase their utility from it. This happens again at step 54.

2.4.2 Flow of Commodities

Typically, a simulation with 3 specialised agents and 3 commodities displays a commodity flow as illustrated in figure 2.9.

This is where agent A_1 trades commodity C_1 for commodity C_2 from agent A_2 and commodity C_3 from agent A_3. The same goes for agent A_2 and A_3 also.

Chapter 3

Adapting Barter Strategies

3.1 Plan

The plan for this experiment is to find an efficient barter strategy. This will be done by fixing the agents barter strategies to the sensible one defined in section 2.3.4, except for one, which we will evolve. The agent's efforts will also stay the same through out the experiment. Effectively we are freezing everything except for one agent's barter strategy.

3.2 Setup

This simulation is set up with 2 agents with the sensible barter strategy from chapter 2 and 2 commodities. The agents start specialised. The simulation is run with the following values, where U refers to the agent's utility at the start of each simulation:

Agent	T_1	T_2	C_1	C_2	U
A_1	1.98	0.01	6.243	0.010	-1.200
A_2	0.01	1.98	0.010	6.243	-1.200
Total	2.00	2.00	6.253	6.253	-2.400

The simulation will be run 10 times and the resulting barter strategy will be recorded.

3.3 Results

The table below shows the results of each run of the simulation. The "Sim No" refers to the simulation number, I refers to the agents response to the offer class and U refers to the agents utility at the end of the simulation. The data is ordered by the agents U ascending.

Sim No	I_1	I_2	I_3	I_4	U
8	0.09988	-0.00003	-0.00991	-0.00007	1.23788
6	0.09994	0.00026	-0.00998	-0.00009	1.27403
7	0.10022	-0.00008	-0.01022	-0.00009	1.28316
9	0.10000	0.00026	-0.00993	-0.00009	1.30750
10	0.10000	0.00026	-0.00993	-0.00009	1.31686
2	0.10024	-0.00009	-0.00979	-0.00009	1.32043
4	0.09994	-0.00017	-0.00990	-0.00009	1.34458
1	0.09974	-0.00005	-0.00978	-0.00009	1.34796
5	0.10005	-0.00002	-0.00992	-0.00010	1.52417
3	0.09986	-0.00001	-0.00994	-0.00010	1.52462

3.4 Explanation

There are 10 different barter strategies listed in the table above. The U column, represents how well the agent that has adopted the strategy has performed.

The higher the value of U, the better an agent has performed. For values above x, this means that the agent has traded less of its own commodities for more in return. This effectively means that the agent has traded for more profit than the other agent.

The trade summary for experiment 3 (using the most efficient strategy) was:

```
Agent 1 gave 0.0764 of commodity 1 to agent 2
Agent 1 received 5.354 of commodity 2 from agent 2
Agent 2 received 0.0764 of commodity 1 from agent 1
Agent 2 gave 5.354 of commodity 2 to agent 1
```

Given that there is an even amount of commodities C_1 and C_2, if the agents were both using the sensible strategy described in chapter 2, the agents would have exchanged an even amount of commodities. As agent A_1 is using the adapted strategy, the agents stabilised with the following values:

Agent	C_1	C_2	U
A_1	6.249	5.364	1.525
A_2	0.086	0.962	-1.080

As seen in the table above agent A_1 has almost all of the commodities in the simulation. This is represented in the two agent's utilities. This is a very aggressive bartering strategy.

The strategies are all very similar with the only significant difference between them being that I_2 is a mix of positive and negative numbers. This is expected as the offer class I_2 is defined as when the offer is below the agents best true offer, but the partner agent is still not interested (See section 2.3.4 for more details).

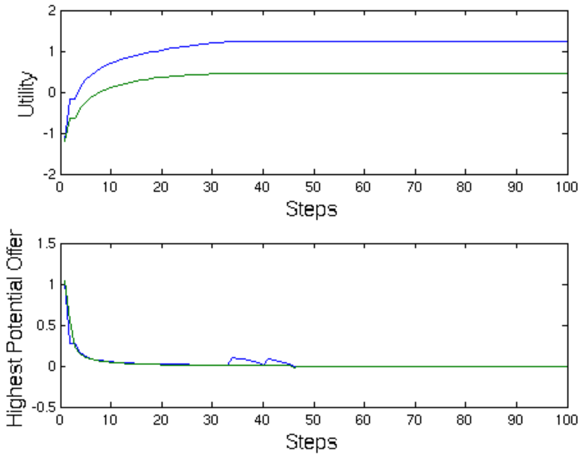

Figure 3.1: Adapting barter strategies, sim No 8 (worst performing of the best 10)

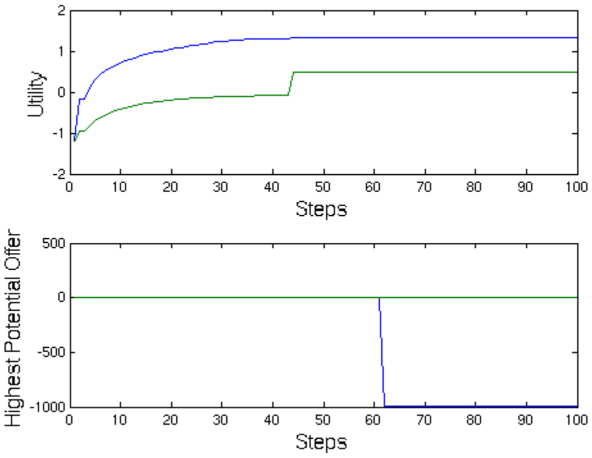

Figure 3.2: Adapting barter strategies, sim No 10 (middle performer of best 10)

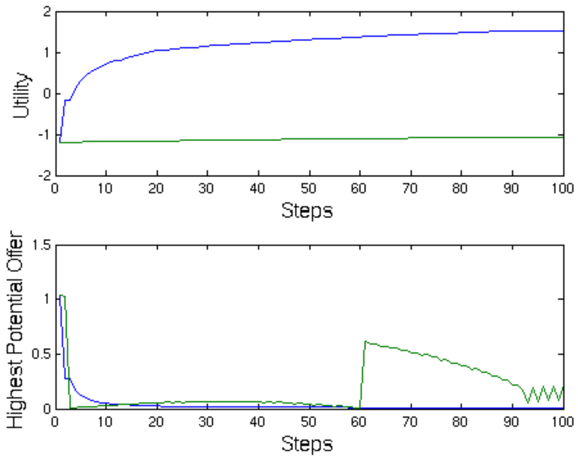

Figure 3.3: Adapting barter strategies, sim No 3 (best performing of the best 10)

The offer class I_4 of the barter strategy is also in ascending order. The higher the value of I_4 then the higher the value of U. ie. If the agents partners flag is set and is no better than the best live trade ($G = G_{best}$), then the agents decrease it current offer by I_4. The more negative the value of I_4, the greater the agent will drop the offer to its partner.

3.5 Discussion

Utility is critically dependent on the barter strategy. Even a very small change in the barter strategy results in a massive change in the resulting utility.

This could be a genuine feature of bartering, or it could be an artifact of this model. This could be because of the hard threshold based decisions for the 4 offer classes. This is interesting, but problematic for investigating specialisation in our model. There is a danger of the barter strategy over shadowing specialisation.

There is much more that could be said about barter strategies. However I have decided to focus instead on specialisation. Therefore, from here on, we will use the simple barter strategy defined in section 2.3.4.

Chapter 4

Simulating Specialisation

4.1 Plan

In order to simulate specialisation a sensible barter strategy will be used. This barter strategy will be fixed for all agents and will not change from generation to generation. A simulation successfully simulating specialisation should be able to start with 3 agents and 3 commodities in an equilibrium state and end in agents in a specialised state.

In order for agents to evolve into a specialised state, an agents efforts will be modified at the end of each run. This modification consists of taking a random small amount of effort from one commodity and putting it towards another commodity chosen at random. This agent is select using the Roulette wheel selection scheme.

4.2 Roulette Wheel Selection

The selection scheme used in this model is the roulette wheel scheme. The roulette wheel chooses an agent that will be selected for evolution. This process is carried out once a simulated run is finished.

The first step is to give each agent a fitness. This is the chance that the agent will be evolved. Ideally we want an agent that did not perform well during the simulation to be selected. Therefore we need an exponential function that allows for this.

$$F = e^{-0.2U} \times C$$

Where F is the chance of an agent being selected, U is the agents utility and C is a constant that helps to scale the function. The higher fitness level, the more chance an agent has of being chosen. The lower the fitness level the less chance an agent has of being selected.

The next step is to find the sum of all the fitness values. Once this is found, we have the ability to find the probability of an agent being selected.

The agents are then ordered from smallest to largest based on their fitness. From this order, it is possible to see each agent's chance of being selected. This chance is directly related to how big the agent's chunk is in relation to the sum of all the fitness.

Agent	Utility	Fitness
A_1	0	10.000
A_2	1	8.187
A_3	5	3.678
A_4	7	2.466
Total	13	24.332

Figure 4.1: Roulette Wheel example values, C = 10

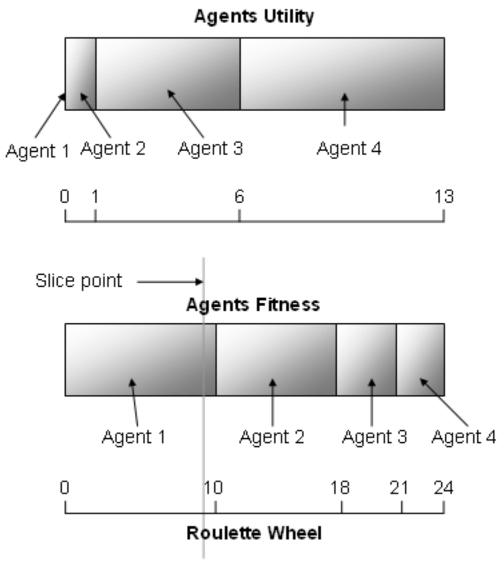

Figure 4.2: Roulette Wheel example

In order to choose an agent a random number between 0 and the sum of the finesses is selected. This is effectively ”spinning the wheel”, where the name of the scheme came from, and the random number selects where the wheel stops. Where ever this is, is the agent that gets selected.

4.2.1 Example

For example, we have 4 agents with values as defined in figure 4.1. Now that the roulette wheel is set up, we spin it. We do this by choosing a random number between 0 and 24.332 (sum of the fitness values). The random number defines a slice point within the population. The agent that the slice cuts through is the agent that the roulette wheel scheme has chosen.

In this case the random number is 8.930, which is our slice point. This point cuts through agent 1. This means that the roulette scheme has chosen agent 1.

From figure 4.2 it is possible to see that the agents that have a lower utility, have a larger fitness. Therefore they have a greater chance of being selected.

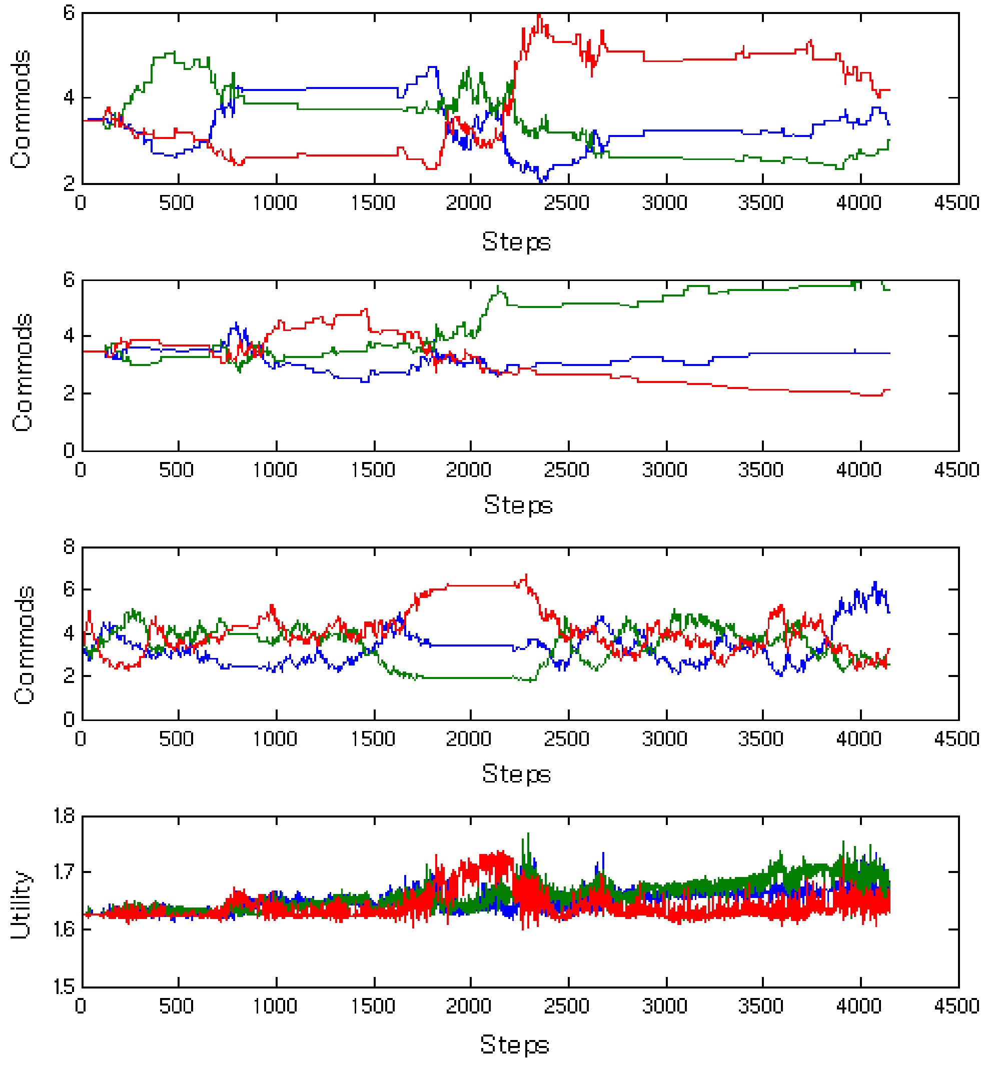

Figure 4.3: Specialisation based on Individual Agents

4.3 Evolution Based on Individual Agents

4.3.1 Evolution

This experiment will use the Roulette wheel to choose an agent that is not performing very well and evolve it. This is done by randomly changing its efforts a small amount.

4.3.2 Setup

This simulation is set up with 3 agents and 3 commodities. The agents start self sufficient, that is, that they start in equilibrium. The simulation is run with the following values:

Agent	T_1	T_2	T_3	C_1	C_2	C_3	U
A_1	1	1	1	1.718	1.718	1.718	0.705
A_2	1	1	1	1.718	1.718	1.718	0.705
A_3	1	1	1	1.718	1.718	1.718	0.705

4.3.3 Results

The simulation is run and the agents struggle to successfully maintain their specialised state. This is evident in figure 4.3. This figure shows each agents commodity levels and their utility.

The top three graphs are of each agents commodities. The blue, green and red lines show C_1, C_2 and C_3 respectively. The bottom graph is the agent's utility, at the end of each run. Blue, green and red lines represent agents A_1, A_2 and A_3 respectively.

From these graphs of the simulation we can see that the agents try to specialise, but get pulled back to an equilibrium (even spread of efforts) state. This is especially evident from step 3000 on. A_1 and A_2 are on their way to a specialised state. But as A_3 joins them, A_1 begins to come back to an equilibrium state.

4.3.4 Explanation

Once all the agents get close to a specialised state it becomes difficult for any one agent to improve any more. However it is to a single agent's advantage to regress back into an equilibrium state. We will explore this further.

We can set up a simulation with 3 agents and 3 commodities and see what happens when all the agents are specialised except one, which is in an equilibrium state. The agent efforts look as follows:

Agent	T_1	T_2	T_3	C_1	C_2	C_3	U
A_1	2.98	0.01	0.01	18.688	0.010	0.010	-2.724
A_2	0.01	2.98	0.01	0.010	18.688	0.010	-2.724
A_3	1.00	1.00	1.00	1.718	1.718	1.718	0.705
Total	3.00	3.00	1.02	20.416	20.416	1.738	-4.743

This table shows that agent A_1 and A_2 are specialised in commodities C_1 and C_2 respectively. Agent A_3 however is in the equilibrium state and has an even spread of efforts. These parameters result in the following summary of trades:

```
Agent 1 gave 6.7 of commodity 1 to agent 2
Agent 1 gave 2.7 of commodity 1 to agent 3
Agent 1 received 6.7 of commodity 2 from agent 2
Agent 1 received 2.5 of commodity 2 from agent 3
Agent 1 received 0.09 of commodity 3 from agent 3

Agent 2 received 6.7 of commodity 1 from agent 1
Agent 2 received 1.2 of commodity 1 from agent 3
Agent 2 gave 6.7 of commodity 2 to agent 1
Agent 2 gave 4 of commodity 2 to agent 3

Agent 3 received 2.7 of commodity 1 from agent 1
Agent 3 gave 1.2 of commodity 1 to agent 2
Agent 3 gave 2.5 of commodity 2 to agent 1
Agent 3 received 4 of commodity 2 from agent 2
Agent 3 gave 0.09 of commodity 3 to agent 1
```

This leaves the agents in the following state:

Agent	C_1	C_2	C_3	U
A_1	9.288	9.210	0.100	0.932
A_2	7.910	7.988	0.001	-0.197
A_3	3.218	3.218	1.628	1.229

In this simulation there is an imbalance of commodities. Due to the utility function, the more of a commodity an agent has the less valuable it is. Therefore the very small about of C_3 in this simulation is a very valued commodity when compared to C_1 and C_2. This means that A_3 can trade very small amounts of C_3 for large amounts of C_1 and C_2.

This is exactly what A_3 did. If we look at the difference in A_3 commodities from the start to the finish of the simulation we can see that A_3 received 1.438 of C_1 and C_2 but only gave 0.09 of C_3 in return.

As shown above, it is greatly to the advantage of a single agent to head towards an equilibrium state while other agents in the population are in a specialised state.

4.4 Evolution Based on Population

4.4.1 Setup

This simulation is set up with 3 agents and 3 commodities. The agents start self sufficient, that is, that they start in equilibrium. This is the same setup as in the previous experiment. The simulation is run with the following values:

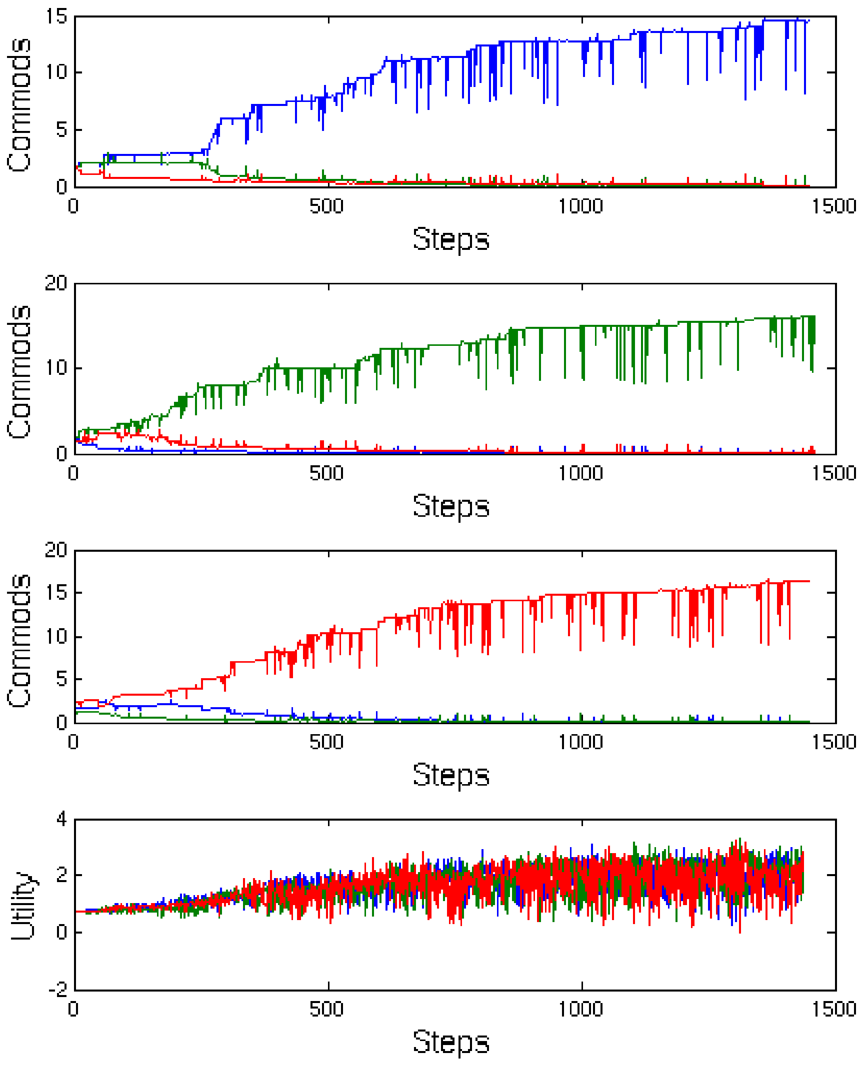

Figure 4.4: Specialisation based on the Population

Agent	T_1	T_2	T_3	C_1	C_2	C_3	U
A_1	1	1	1	1.718	1.718	1.718	0.705
A_2	1	1	1	1.718	1.718	1.718	0.705
A_3	1	1	1	1.718	1.718	1.718	0.705

In this experiment, the agent that is selected to be mutated is only allowed to keep its mutation if the whole population performs better in the next run. In other words an agent can only keep its mutation if it is beneficial to the population.

This is different from the previous experiment as an agents utility may decrease after a mutation, but if the populations utility increases, then this is acceptable. Where the last experiment was based on an individual agent's utility, and a mutation was only acceptable if that single agent's utility increased irrespective of the population.

4.4.2 Results

The simulation is run and the agents successfully move towards and maintain their specialised state. This is evident in figure 4.4. This figure shows each agents commodity levels and their utility.

The top three graphs of this figure are of each agents commodities. The blue, green and red lines show C_1, C_2 and C_3 respectively. The bottom graph is the agent's utility, at the end of each run. Blue, green and red lines represent agents A_1, A_2 and A_3 respectively.

From these graphs of the simulation we can see that the agents reach a stable state of specialisation.

4.4.3 Explanation

In this experiment the agents have no choice but to do what is best for the population. Using this, the agents cooperate and all move towards a specialised state.

4.5 Observed Emergent Mutualisms

4.5.1 Individual Based

With the model that has been described, when an agent is searching for a combination of efforts that will allow it increase its utility within a population of agents that are specialised it will turn to non-specialised or equilibrium state.

As this agent returns to an equilibrium state, its utility increases. Once this agent's utility exceeds the other agent's utility, they then begin to follow suit and start to non-specialise as well. This is due to the fact that this agent significantly drops the production of the commodity that it was specialised in, dramatically increasing the value of it.

The other agents then find that it is cheaper for them to start producing this commodity rather than trading for it as it has become so expensive. This happens until all the agents are in an equilibrium state.

Once all agents come close to reaching the equilibrium state they begin to specialise again and the process starts all over. This unstable behaviour stops the agents from reaching an end state.

4.5.2 Population Based

In the population based experiment the agents do what is best for the population as a whole. As illustrated in figure 4.4, an agent's best strategy for what is best for the population is for each agent to specialise in their own commodity.

Each agent's utility not only depends on what it produces, but also on what other agents produce. That is if any of the agents in the population based experiment suddenly died and hence stopped producing commodities, then the agents left would suffer utility loss.

4.5.3 General

The results of these two experiments show that the model described in chapter 2 produces the Prisoners' Dilemma[6]. This is illustrated in figure 4.5. An agent can typically be described as being in one of two states, specialised or equilibrium.

Two agents can cooperate and work together by specialising in two different commodities and then trading them. This produces the optimal strategy for any two agents, given two commodities. This is illustrated in figure 4.6.

If two agents do not cooperate and do not trade then they must be in an equilibrium state in order to have the highest level of utility. This is an agent's best strategy when it is not relying on other agents.

If two agents are in an equilibrium state, then it is beneficial to them both to try and specialise in a single different commodity each. If the agents are motivated by greed then they will try to out specialise each other. This competition forces the specialisation state upon the agents. The agents benefit from this and their utility increases. This is also true if the agents are motivated by the successfulness of the population.

However, if there are two agents, A_1 and A_2 and agent A_1 is more specialised than agent A_2, and agent A_2 is greedy, it will try any strategy it can to become more successful than agent A_1. As it becomes harder to specialise in a commodity, agent A_2 gives up on trying to be more specialised than agent A_1. Agent A_2 finds that if it starts to fall back into an equilibrium state. Because of this agent A_1 can no longer support itself without agent A_2. This gives agent A_2 and edge and allows it to surpass agent A_1. As agent A_1 is greedy also, it falls back into the specialised state too. This is illustrated in figure 4.7.

It is most beneficial for all agents if they work together. If agent A_1 tries to work with agent A_2, but agent A_2 refuses to work with agent A_1 then agent A_1 gets its utility severely decreased. If both agents do not try to work with each other then they do alright, but not as good as if they were working together.

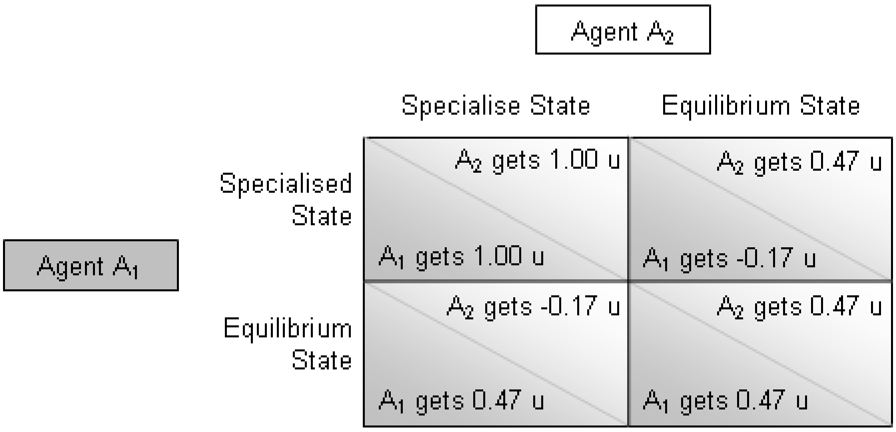

Figure 4.5: The Prisoners' Dilemma. Each agents potential utility u, depends on both agent A_1 and agent A_2s decision to enter a specialised or equilibrium state. Where $\sum_i T_i = 2$.

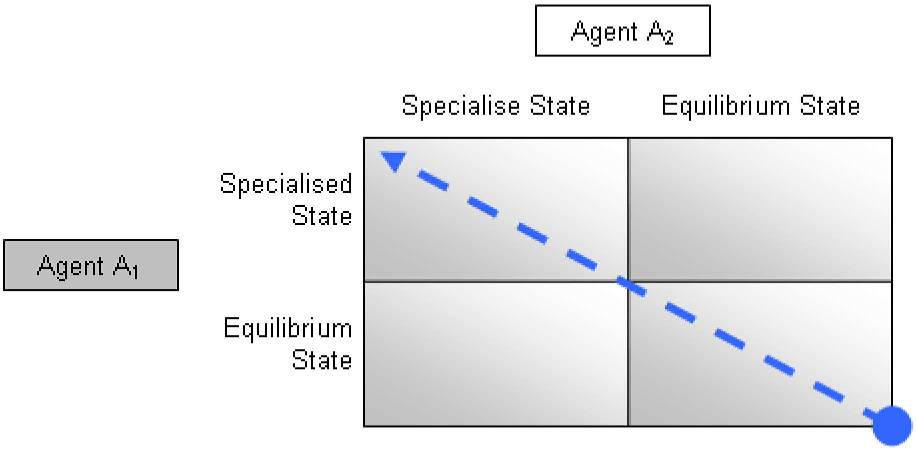

Figure 4.6: The prisoners' Dilemma. Agents are non-greedy or are population based.

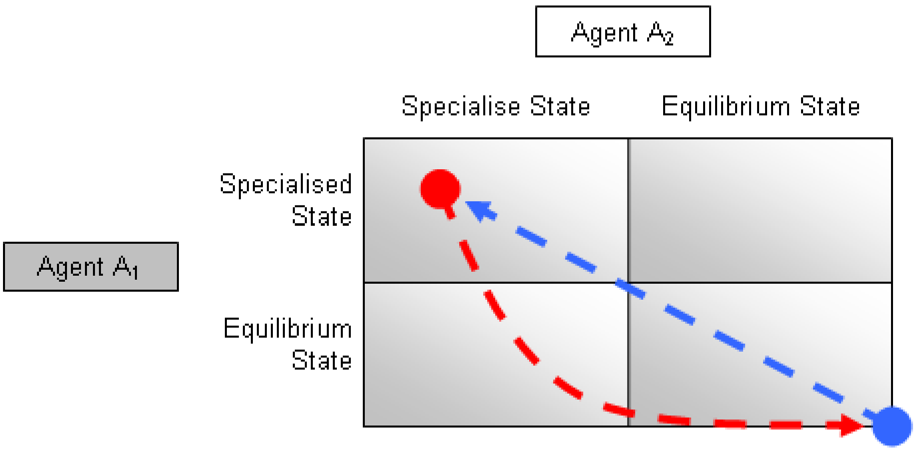

Figure 4.7: The Prisoners' Dilemma. Agents are greedy or are individual based.

Chapter 5

Summary

In this report we have defined a very simple model of bartering. This model is designed to encourage specialisation. This model is set up in such a way that without trade, agents are motivated to be self sufficient. But with trade, the agents have the possibility to do better.

In chapter 2 we have defined a bartering model. This model consists of agents, commodities, trades, offers and flags. In this chapter we also define a simple barter strategy. We have tested the model with 2 agents and 2 commodities, multiple agents and 2 commodities and multiple agents and multiple commodities.

In chapter 3 we looked at adapting the simple barter strategy defined in chapter 2 and finding several that are better. There is a lot that can be said about the barter strategies but, for this report I have decided to focus instead on specialisation. Barter strategies could be looked at in future works, however.

In chapter 4 we look at simulating specialisation in an agent based and population based simulation. The results of these two experiments show the emergence of the Prisoners' Dilemma. The agents are unable to find a stable state in the agent based simulation, but are in the population based simulation.

Agents are most productive when they are cooperating and specialising. However this fails if the agents are also focused on being the best agent.

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