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Peer–to–Peer Bartering: Swapping Amongst Self–interested Agents

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Contents

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Abstract

Large–scale distributed environments can be seen as a conflict between the *selfish* aims of their participants and the group welfare of the population as a whole. In order to regulate the behaviour of these participants it is often necessary to introduce mechanisms that provide *incentives* and stimulate *cooperative behaviour* in order to mitigate for the resultant potentially undesirable availability outcomes which could arise from individual actions.

The history of economics contains a wide variety of incentive patterns for *cooperation*. In this thesis, we adopt *bartering* incentive pattern as an attractive foundation for a simple and robust form of exchange to *re–allocate resources*. While bartering is arguably the world's oldest form of trade, there are still many instances where it surprises us. The success and survivability of the barter mechanisms adds to its attractiveness as a model to study.

In this thesis we have derived three relevant scenarios where a bartering approach is applied. Starting from a common model of bartering:

- We show the price to be paid for dealing with *selfish agents* in a bartering environment, as well as the impact on performance parameters such as topology and disclosed information.

- We show how agents, by means of bartering, can achieve gains in goods without altruistic agents needing to be present.

- We apply a bartering–based approach to a real application – Internet directory services.

The core of this research is the analysis of bartering in the *Internet Age*. In previous times, usually economies dominated by bartering have suffered from high *transaction costs* (i.e. the improbability of the wants, needs that cause a transaction occurring at the same time and place). Today, the world has a global system of interconnected computer networks called Internet. This interconnected world has the ability to overcome many of the challenges of previous times. This thesis analyses the oldest system of trade within the context of this new paradigm. In this thesis we aim to show that bartering

has a great potential, but that there are many challenges that can affect the realistic application of bartering which should be studied.

Resumen

Entornos distribuidos y a gran escala pueden ser un punto de conflicto entre los objetivos egoístas de sus participantes y el bienestar de la población. Con la idea de regular el comportamiento de los participantes en el sistema, es necesario introducir mecanismos que fomenten *incentivas* y estimulen un *comportamiento cooperativo* con el objetivo de compensar la impredecible disponibilidad de recursos.

La historia de la economía contiene una gran variedad de patrones para incentivar la *cooperación*. Nosotros nos centraremos en el patrón de *intercambio* (i.e. trueque) por su simplicidad y robustez como forma de re–asignar recursos. Mientras podemos asegurar que el intercambio es la forma más antigua de intercambio, aún existen muchos ejemplos donde éste puede sorprendernos. El éxito y la supervivencia de los mecánismos de intercambio añade atractivo al estudio de este modelo.

En esta tesis hemos creado tres escenarios relevantes donde se ha aplicado el intercambio. Todos ellos partiendo de un mismo modelo de intercambio, tenemos:

- La exploración de características y viabilidad de un mercado de intercambio comparando su rendimiento,
- Mostrar un sistema de intercambio con una población no altruista y con diferentes tipos de poblaciones,
- Aplicar un sistema de intercambio a una aplicación real como es el servicio de directorios.

El núcleo de la investigación es el análisis del sistema de intercambios en la *época de Internet*. En épocas previas solía suceder que una economía dominada por el intercambio sufriera un elevado *coste de transacción* (la imposibilidad de que los deseos y necesidades que provocan una transacción ocurran en un tiempo y lugar determinado). Hoy en día, el mundo dispone de un sistema global de interconexión de redes de ordenadores llamado Internet. Este mundo interconectado ofrece nuevas oportunidades para superar las

limitaciones de una economía de intercambio. Esta tesis analiza el sistema más antiguo de negociación en este nuevo paradigma. Mostrando que el intercambio tiene un gran potencial, pero que al mismo tiempo, deben ser revisados una gran cantidad de desafios que pueden afectar a su aplicación. El trabajo se ha focalizado en la experimentación y la extensión de un conjunto de escenarios donde se realiza economía de intercambio.

PART 1: Context and Background

Chapter 1

Introduction

In August 2000 the world's economic leaders met for an annual policy conference in Jackson Hole, Wyoming. Alan Greenspan was there, as were the heads of the central banks of Britain, Japan, and 26 other countries.

One of the attendees, Mervyn King, Deputy Governor of the Bank of England, ruminated on the impact of electronic commerce and the future of money. His conclusion, quoted below, was be startling to some:

- "There is no reason that products and services could not be swapped directly by consumers and producers through a system of direct exchange–essentially a massive barter economy.

- All it requires is some commonly used unit of account and adequate computing power to make sure all transactions could be settled immediately.

- People would pay each other electronically, without the payment being routed through anything that we would currently recognise as a bank. Central banks in their present form would no longer exist–nor would money."

A standard dictionary defines *barter* as trading goods or services without the exchange of money. This is conducted between parties who have products or services that each other need or want. The keyword here is *need*. Barter has survived to this day. Why? Simply because people needed it then, as they need it now, only the methods have changed over time.

In the days before the Internet, skilled business owners performed barter exchanges mostly by word-of-mouth, choosing to approach others in other trades based in a large part on the recommendations of business owners they knew and trusted. At present barter has been used in situations of economic crises, as in U.S. or recently in Argentina[1]. In these situations, money loses its value and obtaining goods requires the use of other means. In this context barter offers up a way to interchange goods with similar values. However, bartering has many other sides where it is relevant. This thesis explores cases where bartering could be applied. The thesis first develops a common model for bartering amongst electronic entities and then explores a number of different bartering scenarios with diverse and exclusive properties. Starting each case from the same model, specific properties are studied. Results are subsequently and verified by means of simulations and analysis which to explore the dynamics underlying each scenario and the validity of the model is checked.

In human society, resource re–allocations are, in most cases, performed through markets. This occurs on many different levels and in many different scales, from our daily grocery shopping to large trades between big companies and/or nations. Barter has been used as many times as ways to supply the needs of developing societies.

Old Meets New: The large–scale barter networks – In the modern day, the advent of computers not only revolutionised the world, it also facilitated a sudden resurgence of bartering. The tremendous capabilities of this new technology of tracking barter transactions and maintaining huge inventories made bartering an easy and inexpensive form of trading. Today, it is amazing to see what can be obtained through bartering: computer hardware and software, household items, jewellery, books, CDs, movies, hotel accommodations, etc. The list is endless. Barter is a big business and getting bigger with every passing day.

Several modern barter tales illustrate the growing sophistication and resurgence of the barter. Some examples of exciting transactions:[2]

- A broker arranged the exchange of 500 Fujitsu laser printers for 1.7 million units of military ready-to-eat (RTE) meals, which were in turn sold to relief agencies for immediate use in hurricane-ravaged Florida and Hawaii. The RTEs were surplus from the Persian Gulf conflict.

- In the largest trade deal ever inked between a U.S. corporation and the former Soviet Union, PepsiCo, Inc. agreed in April 1990 to renew its agreement to trade Pepsi-Cola concentrate syrup for Stolichnaya Russian vodka until the year 2000 – a pact worth more than $3 billion in total retail sales. Several innovative countertrade mechanisms will allow PepsiCo to use foreign exchange credits from vodka sales to build dozens

[1] Argentines barter to survive http://news.bbc.co.uk/2/hi/business/1977804.stm
[2] Behind the barter boom by Rod Willis in http://www.allbusiness.com

of bottling plants and several Pizza Hut restaurants in the Coalition of Independent States.

- New York City's Lexington Hotel obtained a sophisticated computer system for almost nothing. In 1991, a barter firm gave the hotel money to buy the computers in exchange for more than $300,000 in room credits that the firm could use or, with the hotel's approval, sell or barter for other goods or services.

- Another recent innovation is bartering goods and services for excess office space. Both SGD and ICON[3] trade advertising time, hotel rooms, or office equipment, among other goods and services, for unused space.

- Occasionally, barter gets amazing deals as the legendary purchase of an island by Peter Minuit, who in 1626 bartered trade goods valued at 60 gold coins for an island called Manhattan.

One of the most visible examples of electronic bartering today is the use of peer–to–peer technology to complete multi–party barter exchanges in file sharing applications. The bartering strategy ensures that for a peer the amount of incoming data is roughly equal to the amount of outgoing data. The use of mass collaborative network exchanges goes from public to private environments. In this latter, to get an account it is necessary to know someone who is already a member (e.g. funfile[4], pretome[5], stmusic[6]). File–swapping networks have been used for:

- Changed the values of music and its a role in the music industry's future

- Diffusion of films and TV shows

- Distribution of patches and upgrades

With the Internet which is inherently global, bartering could change the face of global e–commerce. The Internet reintroduced bartering back into our economic systems. Being capable of connecting an infinite number of traders and opening an unlimited opportunity for trade partners.

[3]ICON in http://www.icon-intl.com
[4]Funfile in http://www.funfile.org
[5]Pretome in http://pretome.net
[6]Stmusic in http://www.stmusic.org

1.1 Motivation

Exchange represents the basis of human economic behaviour and is pervasive in Social and Artificial Societies. Many different areas are involved in exchange theory:

- **Sociology:** The premise that all social life can be treated as an exchange of rewards or resources between actors. See [24], [107].
- **Politics:** Exchanges between citizens and holders of political authority.[146]
- **Economics:** Money and services are exchanged for goods.
- **Artificial Societies:** Exchange of digital items or resources has been identified in Artificial Societies such as P2P [12], Grid [194], and MAS [126].

Barter has been used as system of exchange by ancient and modern civilisations. Also, barter is widely applicable in setting of distributed Artificial Societies with examples present in many different areas such as file sharing [7], query forwarding [31], routing [23], knowledge diffusion ([47], [127]), storage–sharing systems ([46], [49], [56], [140]), and WIFI hotspot sharing [62]. It is applied in commercial platforms like Linspot[7], Netshare[8] or Fon[9]. Barter has also been used in B2B commerce with many others examples such as BizXchange, ITEX, BarterCard and Continental Trade Exchange. Many hopes are riding on barter mechanisms in the Internet Age. From [123] and [184]:

"Is it possible that advances in technology will mean that the arbitrary assumptions necessary to introduce money into rigourous theoretical models will become redundant, and that the world will come to resemble a pure exchange economy? Electronic settlements in real time hold out that possibility."

Nicholas Negroponte puts it as follows:

"A parallel and more intriguing form of trade in the future will be barter. Swapping is a very attractive form of exchange because each party uses a currency that is devalued for them i.e. an unwanted possession, that otherwise would be wasted. The most stunning change will be peer–to–peer, and peer–to–peer–to–peer- ... transaction of goods and services. While this is nearly impossible to do in the physical world, it is trivial in cyberspace. Add

[7]Linspot by Biontrix http://www.linspot.com

[8]Netshare by Speakeasy Inc. http://www.speakeasy.net/netshare

[9]Fon in http://www.fon.com

the fact that some goods and services themselves can be in digital form, and it gets easier and more likely."

Bartering is an attractive model to study in distributed environments such as P2P–Networks, Ad–Hoc Networks and Multi–Agent Systems and other forms of peer production. These offer clear examples of large–scale environments which apply effective bartering practices. These communities consist of autonomous entities that need cooperation to exploit participant's resources. Without proper incentive mechanisms, a system may become useless because entities may engage selfish behaviour. To counterbalance this, external incentives for cooperation are indispensable. In this thesis, a bartering approach is considered as an incentive scheme. See [29], [81].

From a technical point of view, the work draws together results from the following fields:

- Market Dynamics.
- Dynamics of economic Networks.
- Complexity and Markets.
- Economic Models.
- Agent–Based Simulation.
- Scalability and performance issues.
- Cooperation, Competition and Autonomy.
- Self–Organization/Adaptation of Multi–Agent Systems.
- Peer–to–peer, Grid and other open distributed systems.
- Novel applications.

The thesis is divided into three related parts with a common aim:

- **A bartering framework:** Resource allocation amongst selfish, rational and autonomous agents.
- **A bartering phenomena:** A sequence of bartering exchanges that turn a paperclip into a house.
- **A bartering application:** A distributed barter–based directory services.

These parts have a high degree of complexity associated with them because:

- As one may imagine, the barter principle strongly constrains the design of a content–distribution algorithm. The efficiency–loss incurred is the price to be paid for dealing with selfish agents as opposed to cooperative ones, and the way to trade, in our case a bartering approach.[76]
- Searching a path from lower values to higher values items in domains with selfish and dynamic entities.
- The collection of challenging characteristics and competing entities (i.e. popularity and scarcity of resources) that inhabit the environment.

The general approach taken to investigate the many hopes on bartering by means of development of theoretical framework, and system building and assessment.

1.2 Contributions

This thesis has been focused on investigating resource allocation using a bartering mechanism, with particular emphasis on applications in large–scale distributed systems, without the presence of altruistic participants in the environment. In addition to the individual summaries that are located at the end of each chapter, we also want to sum up briefly the content of this thesis as a whole. The most significant contribution of this research are as follows:

- **General Framework:** A representation of the functioning of a bartering system. The design and development of a general framework applied to three specific scenarios. Each one of these help us to show that bartering is more in use than ever:
  - Developing a barter network in order to review the efficiency of bartering.
  - Developing a simple agent population model based on active and passive agents with ranges of personal value without altruism.
  - Design, implementation and evaluation of a distributed directory services based on a bartering mechanism.
- **Bartering Networks:** Comparison of the performance of bartering algorithms with respect to the optimal one and the influence of information on efficiency.

- **Trading Paperclips:** Demonstration of the trading up process by finding beneficial chain of trades.

- **Distributed Barter–Based Directory Services:** The application of bartering to a core network service such as directory services.

1.3 Structure of the Thesis

The thesis is structured into 9 chapters which are grouped in 3 parts. The first part consists of this current introduction together with the chapter that maps out the methods used and a literature review. The second part is the backbone of the thesis. In this part, the problem, implementation, and results are discussed. The four chapters that make up this part are technical chapters. In the first, a framework is developed which, over the next three chapters, develops bartering scenarios. The last part contains the contributions, conclusions and future work. Figure 1.1 sketches the order of the thesis. The structure of this thesis is as follows:

- Chapter 1 Introduction, introduces the work and presents the overall picture, of the bartering mechanism.

- Chapter 2 Bartering, shows the definition and challenges of bartering.

- Chapter 3 Methodology, maps out the methods that were utilised.

- Chapter 4 Related Work, reviews related work and how it addresses the presented problems.

- Chapter 5 General Framework and Simulation, describes the conceptual development.

- Chapter 6 Bartering Networks, shows relevant features that have an effect on the performance of the allocation of resources.

- Chapter 7 Trading Paperclips, describes and extends the story of Kyle MacDonald.

- Chapter 8 Distributed Barter–Based Directory Services, develops a bartering application.

- Chapter 9 Contributions and Conclusions, presents specific conclusions drawn from the results of each stage of the investigation in earlier chapters.

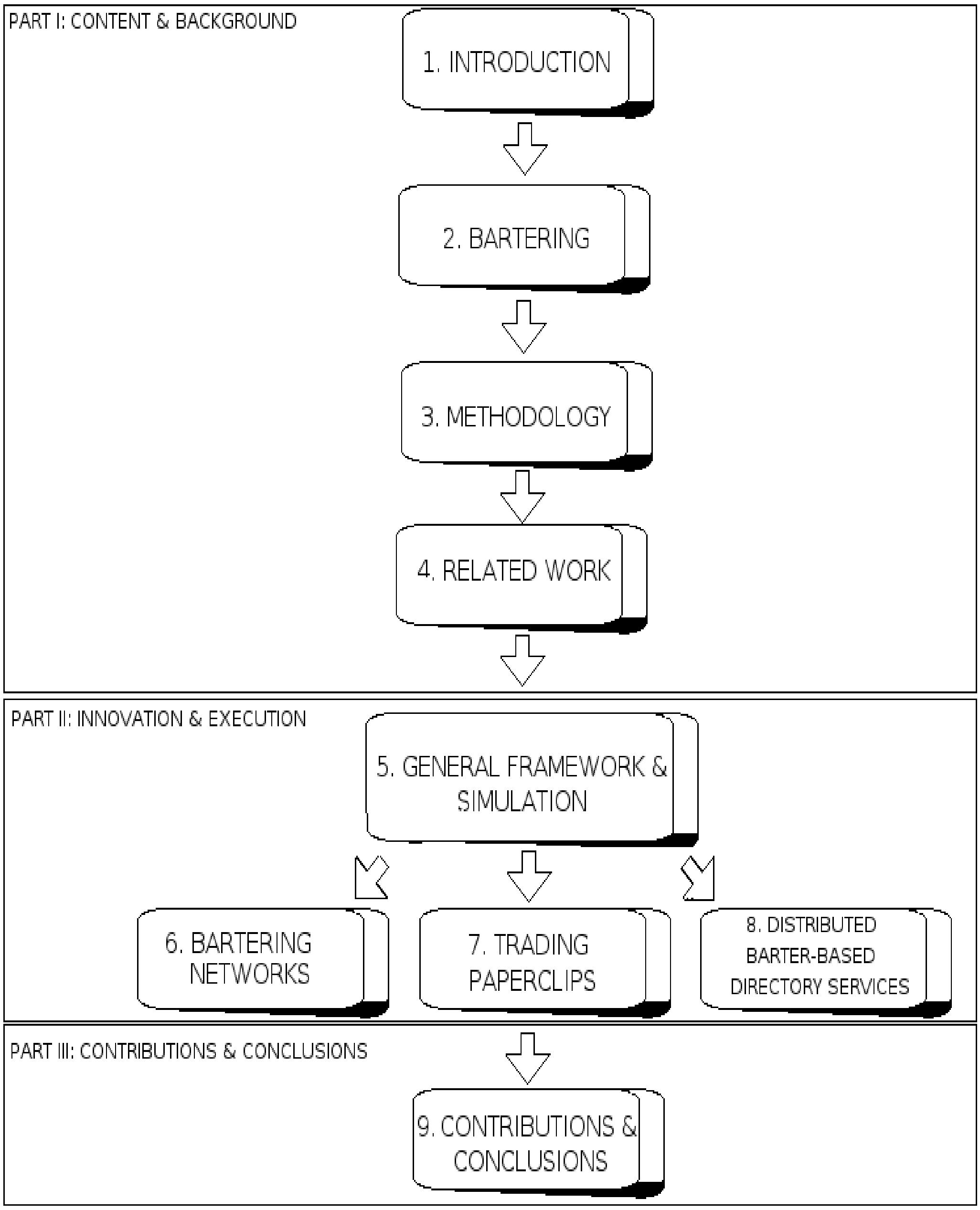


Figure 1.1: Thesis structure.

Chapter 2

Bartering

The work in this chapter investigates interactions amongst *selfish*, *rational*, and *autonomous* agents in resource allocation, each one with incomplete information about other entities, and each seeking to maximize its expected utility by means of exchanges in our case bartering. The distribution of a set of items amongst a set of distributed and autonomous agents, with varying preferences, is a complex combinatorial problem.

Bartering could be done by two or more participants. In *restricted exchange*, two actors exchange resources with each other. In other words, the resources that one actor gives are directly contingent on the resources that the other gives in return. If A gives to B, B is the person who would reciprocate to A. This type of exchange is very common. Examples include exchanges between teachers and students, economic transactions, employers and employees, and so on. Most of the social exchange network research that has emerged since the 1980s in sociology focuses only on restricted exchange. Thus, reciprocation is direct.

A different way to relax the barter requirement is to allow *transitive* use of credit (i.e. triangular barter) – A will upload to B if B is simultaneously uploading to C and C is simultaneously uploading to A. We call this triangular barter. This is more flexible than simple barter, since can receive data even if does not have data that is useful to A. Clearly, one could generalize this idea to allow *cyclic barter*, involving cycles of any length – but cheat–proof implementation of this generalization is likely to be complex. Multilateral bartering is more complex but allows trades that would not be possible with bilateral bartering. Complex, because multilateral bartering with even more participants involved in the exchange process, the protocol becomes more difficult to design, but at the same time the large scale of participants increases the opportunities.[11]

In contrast to restricted exchanges, which occur between two actors, *gen-*

eralized exchange inherently involves more than two people. In generalized exchange, there is no one–to–one correspondence between what two actors directly give to and receive from each other. A's giving to B is not reciprocated by B's giving to A, but by C's giving to A, where C is a third party. Thus, reciprocation is indirect, not mutual.[22]

In this thesis, both Trading Paperclips and Distributed Barter–Based Directory Services scenarios follow a restricted exchange pattern. However, Bartering Networks scenario follow both exchange approaches. Because the aim of Bartering Networks is to study the optimal allocation and primitive pair–wise exchange schemes that follows a simple tit–for–tat strategy [42] are performing unsatisfactorily, due to the classic problem of the "double coincidence of wants": "To find two persons whose disposable possessions mutually suit each other's wants. There may be many people wanting, and many possessing those things wanted; but to allow of an act of barter [142], there must be a double coincidence, which will rarely happen. . . . The owner of a house may find it unsuitable, and may have his eye upon another house exactly fitted to his needs. However, even if the owner of this second house wishes to part with it at all, it is exceedingly unlikely that he will exactly reciprocate the feelings of the first owner, and wish to barter houses. Sellers and purchasers can only be made to fit by the use of some commodity . . . which all are willing to receive for a time, so that what is obtained by sale in one case, may be used in purchase in another. This common commodity is called a medium, of exchange, because it forms a third or intermediate term in all acts of commerce." (Jevons, 1876, chap. 1). The second difficulty for the serving peer to predict which one he is serving to would be serving him in the future (i.e. future needs). Thus it has to be unnecessarily generous in giving. And this extra generosity can be exploited by free–riders. To avoid this behaviour our environment assumes that the agents follow a selfish behaviour and by means of the information that they can get from the market, the agents try to avoid the lack of coincidence of wants.[101]

In all the scenarios studied, the agents exchange following a classical symmetric scheme (i.e. imposing upon users to contribute at least as much as they use the system). Bartering as any form of trade requires search, negotiation, and exchange, which are activities that absorb resources.

Properties that are distinctive to bartering and a proper characterization of those features of an application that might make bartering preferable. Demonstrating applicability in specific applications:

- File sharing.
- Peer–to–Peer (P2P) VoIP-PSTN peering.

- P2P backup, query forwarding, hotspot sharing.

Bartering is arguably interesting for the following features.

- Self–regulation.
- Distributiveness.
- Preserves autonomy (i.e. local decision).
- Incentive scheme by nature.
- Robust.
- Simplicity.
- Forces nodes to keep items; making items highly available and less likely to be lost.
- Memory–less and therefore goal focused.
- Anonymity.
- Under–utilized capacity, excess or unsold inventory.

All of these features greatly favour the use of bartering in distributed environments with self–interested participants. However, the major problem of bartering is the inefficient – time consuming search for a double coincidence of wants.

2.1 Bartering Challenges

The three challenges in this case are:

1. **Detection of needs:** In organizational systems where agents have to explore a search space and interact with other agents, information, as preferences and ownership of neighbours, is an indispensable tool in the decision–making process.

2. **Network structure:** Network structure is another determining factor of the utility/*level of satisfaction* (*los*) to the society of involved players. Network exchanges and markets consist of environments containing many interconnected agents interested in buying and selling items. In many realistic situations, agents are only connected to a limited number of other agents, and unable to directly trade with all the

agents that are present in the environment. For instance, a buyer's expected satisfaction from a trade may depend on how many sellers this buyer is negotiating with, together with how many other buyers they are connected to.[48]

3. **Individual interest:** Koutsoupias [37] coined the term "the price of anarchy" to refer to the increase in cost caused by independent selfish behaviour [129] with respect to a *social welfare–maximizing solution.* Classical approaches to the *assignment/allocation problem* (AP) strive for just such a social welfare–maximizing solution. Specifically the problem consists in allocating a finite set of items to a finite set of agents where each agent has a specific satisfaction for each objects. Classical AP only focuses on maximizing the overall social welfare [120], whereas a bartering approach, and more concretely, the competition associated is a good mechanism to promote collaboration.

These three challenges can be detected in multiple scenarios. From P2P networks, which share content amongst peers, to people networks which share items or resources sharing amongst dynamic collections of institutions distributed across the world as in Grid systems.

In order to solve the assignment problem (AP), there are standard optimization methods that provide a solution[1] ([30], [112]). However they make several important assumptions. The first is that allocations are made by a centralized process which A) has access to the preference information of all agents (i.e. knowing the needs/wants of agents or complete information), and B) is empowered to make this allocation. Secondly, the method should take into account the fact that members are fully connected (i.e. assuming that everyone knows everyone) all the time. Thirdly, these methods implicitly assume that agents in the population accept the results of the allocation – even if their own satisfaction may decrease in a particular global solution (i.e. they act in an *altruistic manner* towards the overall population). However, in a distributed environment, where agents try to obtain *maximum benefit* in an independent way, the assumptions accepted by classical AP methods are unrealistic since they deal with the problem of allocation at the community level that assume fully connected topologies and they ignore the autonomy of the individual. The scenario addressed is:

- There are centralized procedures that achieve the optimal allocation;

[1] "Matching", in our case one–side matching, [156] is the part of economics that focuses on the question of who gets what, particularly when the scarce items to be allocated are heterogeneous and indivisible.

- In general, it is not possible to find a decentralized procedure that achieves the optimal allocation.[137]

In systems involving multiple autonomous agents, it is often necessary to decide how scarce resources should be allocated. Moreover, when selfish agents have competing interests, they may have incentive to deviate from protocols or to lie to other agents about their preferences. Against this background, this chapter studies resource allocation in Multi–Agent Systems in which each agent 1) is selfish and 2) has incomplete information about the other entities in the world under a barter–based approach. Barter trade exhibits several characteristics that are desirable in the environment in which we face, i.e.:

- **Anonymity:** The participating entities do not have to disclose their identity.

- **Enforcement:** Bartering is an incentive scheme by nature.

- **Scalability:** The incentive pattern may be effectively applied by a large number of entities.

- **Localization:** Cooperation and remuneration do not require interaction with dedicated entities.

2.2 Bartering Features

Barter transaction between two or more parties has features that are reviewed in this section:

- **Market topologies and structures:** The relationship between participants in a market/barter network can take many different forms. Participants follow rules at the instant of offering items to the market. These rules decide which available items the agent should offer to its neighbours. They are influenced by the items offered in the market. If the market is offering valuable items, the agent is willing to offer its items. When an agent is connected to the rest of the agents in the system (i.e. fully connected topology) it has more opportunities than when an agent has a reduced number of connections. Thus, the fewer neighbours that an agent has, the greater the reduction in the possibility of useful items being offered. This second case could be for several reasons – it could be informational (i.e. certain sellers and buyers are not aware of each other) or institutional (i.e. conventions prohibit certain sellers from transacting with certain buyers) or each buyer could prioritize the sellers somehow, and only be interested in trading with the highest–priority seller.

- **Agent-based distributed resource allocation:** The problem of how to allocate resources in a distributed manner has been addressed since the beginnings of agent–based research. Algorithms or methodologies have been developed that specifically take into account the decentralized system structure of Multi–Agent Systems and their ability to communicate and coordinate. For example, multi-agent system architectures are well suited to dynamic resource allocation. These classes of allocations are defined by their degree of distribution of control and degree of synchronization [33], [52]. Well–known methods of this type include blackboard structures or auction-like algorithms (see [40], [160], [188] for a summary). The method which will be investigated here is based on economic markets, since resource allocation is also a basic problem in Human Societies. See [25], [35], [68].

- **Grid resource allocation:** Resource allocation is the key technology in Grid computing. Economic based grid resource allocation is an area of study due to a lack of resource ownership and control.[95] Projects such as the POPCORN project[2] provide a market-based mechanism for trade in CPU time to motivate processors to provide their CPU cycles for other peoples computations. Nimrod–G[3] is a computational economy-based global Grid resource management and scheduling system that supports deadline and budget constrained algorithms for scheduling parameter sweep applications on distributed resources. In this way, bartering of resources on grids have been studied in different papers [136], and in projects such as Gossiptron [190] and Catallaxy [67].

- **Both-Sided and one-sided matching models:** In cases where both sides of the market have preferences over the other side, a satisfactory answer to this question, called *stable matching*, was proposed by Gale and Shapley (*G–S*) [75]. Since then, this concept was used in many applications including matching medical students to hospitals. One of the most important properties of stable matchings is that they always exist.

[2]POPCORN in http://www.cs.huji.ac.il/∼popcorn/

[3]Nimrod-G in http://www.csse.monash.edu.au/∼davida/nimrod/nimrodg.htm

There are markets where only one side has preference over the other (i.e. one–sided matching). Such markets correspond to situations where one side of the market consists of agents with preferences, and the other side consists of items that can be allocated to the agents. In cases where there is an initial assignment of items to the agents (e.g., in some models of the housing market), there is an algorithm commonly known as the top trading cycle algorithm (TTC) that always finds a solution with satisfaction properties.[167]

Qualities that G–S brings:

- Not necessarily Pareto–optimal.
- Strategy proof.
- Stability – eliminates justified envy.
- A stable matching exists that is preferred to any other stable matching.

Qualities that TTC brings:

- Pareto–efficient.
- Strategy proof.
- Does not eliminate justified envy.

The preferred algorithm will depend on whether it is more important to be fair or to be efficient.

- **Bilateral/pairwise/direct and multilateral exchanges:** Bilateral or multilateral commitments often refer to the mutual provision of services. From an abstract point of view, such mutual provision of services represents an exchange of items [131]. Pairwise exchange is a simple way of bartering, in which two peers directly satisfy each other's needs. Fortunately, we can generalize pairwise exchange to group exchange, by introducing the notion of an *exchange circle*. In a circle, each participant provides content to the next person in the circle, and receives content from the previous person in the circle.

  With respect to the quantity of participants involved in the barter process:

  - In restricted or bilateral/pairwise exchange, two actors exchange resources with each other. In other words, the resources that one actor gives are directly contingent on the resources that the

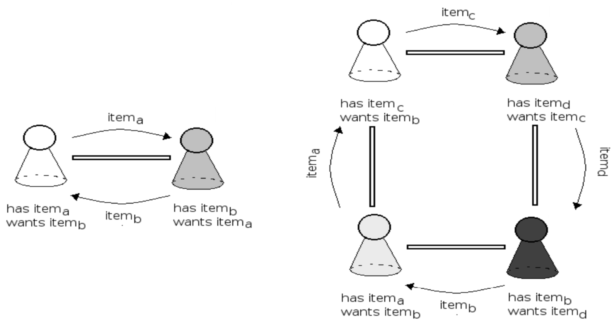


Figure 2.1: Bilateral exchange versus Multilateral exchange.

other gives in return. If A gives to B, B is the person who would reciprocate to A. This type of exchange is very common (see Figure 2.1 a)).[54]

– In contrast to restricted exchanges, which occur between two actors, generalized or multilateral exchange inherently involves more than two people. In generalized exchange, there is no one–to–one correspondence between what two actors directly give to and receive from each other (see Figure 2.1 b)). See [97], [175]. The following list shows features of N–way exchanges:

  * A generalization of barter, which retains some of its simplicity.
  * "Provide to those [who provided to those]* who provided to me".
  * A type of indirect reciprocity (sociology).
  * Scales to larger populations, compared to direct–only exchanges.
  * Does not require (central or distributed) authorities.

General weaknesses related to bartering are:

  * Exchanged items must be of equal value (at least for the personal point of view of their participants).
  * Missing valuation mechanisms ⇒ equal items (e.g. file parts).
  * No possibility to pay for more consumption or to get paid for more contribution.

The *exchange process* is the interaction between buyer and seller in which each participant gives the other something of value. Figure 2.2 shows the interaction between a seller and a buyer in an exchange process. Firstly, the buyer sends the want–list (WL)

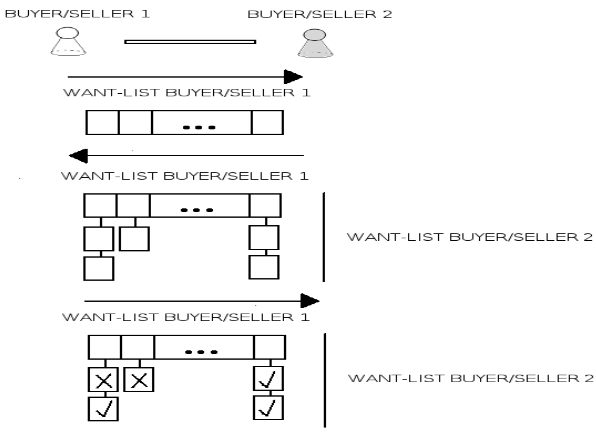


Figure 2.2: Skeleton of the general framework.

to the seller. This is re–send for each item offered. The buyer reviews this list and checks which offers are beneficial or not (i.e. have list HL). Once, the buyer has the list of entries proposed by the seller, and it gets the list of items to exchange, the last task is to make the exchange process. The strategy in the exchange process should be to exchange only the best deal or to make any available exchange.

In any exchange process one of the following situations could occur:

* The exchange moves the goal directed agent nearer/farther to/from the objective item.
* The exchange means that the agent gets something more valuable than the targeted item in terms of general market value.
* The exchange means that the items obtained will never be replaced by other items, breaking the chain of trades or opening a new sub–optimal chain of trades (e.g. the item is one nobody else desires).

The exchange algorithm 1 takes the following steps:

– **Finally we have exchanges with restricted lengths:** Let us suppose that the size of the basic coalitions are restricted. Thus the outcome of the game is an l–way exchange that contains no cycle with length more than l. Obviously, an l–way exchange is equivalent to a vertex–disjoint packing of directed cycles with length at most l. [97] If $l = 2$, so only pairwise exchanges are

Algorithm 1 The exchange algorithm

Step 1: The propagation of advertisements.
$agent_1$: To offer the items to the $agent_2$'s
Step 2: The pairwise matching.
$agent_2$s: To comparison of the PV_{agent_2}(item offered by $agent_1$) of the item offered in step 1 with its PV_{agent_2}(own item)
if PV_{agent_2}(item offered by $agent_1$) $>$ PV_{agent_2}(own item) **then**
  offer any of its own items to $agent_1$
end if
Step 3: The selection of the optimal pairwise matching.
$agent_1$: To choose of the item with a large MV offered in the step 2
Step 4: End conditions for $agent_1$.
if the item has obtained in step 3 is equal to the item desired **then**
  to stop
else
  to go back to step 1
end if

allowed, then the problem becomes a matching problem in an undirected graph G with the same vertex set. In this case, an edge links two vertices if a pairwise exchange is possible between the corresponding pairs.

With respect to the time when is rewarded the participants involves in the barter process:

* **Immediate service in return:** The participants provide a service in return simultaneously.
* **Non-immediate service in return:** Sometimes it is infeasible to give a service in return, in this case the participants promise a service in return.

- **Long or short path:** An interesting question in N–way exchanges is how to choose from different feasible exchanges. In principle, a preference for larger rings should improve overall performance, as more participants are served. On the other hand, participants prefer smaller rings as the search cost is lower, and the expected exchange volume is also higher for smaller rings, as the probability of a peer either disconnecting or completing is higher for larger rings. Assuming participants care less about global performance and more about their own benefit, there is no clear incentive to put additional effort into looking for larger rings when even a two-way exchange has been located. This question is very related to the performance. [7] Also, the multilateral trade has associated a higher transaction cost because all participants should be synchronized. See [58], [64].

- An intrinsic problem that arises is that some of the users who should participate in a proposed path of exchanges may fail because users may learn of a better choice to exchange its items, e.g., a direct exchange with one of the users participating in proposed path.
- Another problem is that an agent could act as a middleman between two agents that could perform an exchange directly with each other, and obtain an object without doing any useful work for the system. Specifically, let us assume that agent A has item_x and wants item_y, and agent B has item_y and wants item_x. The cheating agent C, interested in item_x claims that he has item_y and wants item_x when talking to agent A, and that he has item_x and wants item_y when talking to agent B. Agent C would start getting blocks of item_y from agent B and exchanging them for blocks of item_x with agent A which in turn are passed to agent B for more blocks of agent D. In this scenario, agent C does not contribute any useful work to the system, and can still get high–priority service. If this can happens, then the exchange–based incentives could be broken down.

• **Types of optimal allocations:** Depending on the environment an optimal allocation or other could be achieved (see Figure 2.3):

  - **Initial optimal allocation (IOA):** The allocation in the initial state.
  - **Bilateral optimal allocation (BOA):** A BOA is an allocation that can not be improved upon by bilateral trade.
  - **Multilateral optimal allocation (MOA):** A MOA is an allocation that can not be improved upon by multilateral trade.
  - **Pareto optimal allocation (POA):** A POA is achieved when it is not possible to make anyone better off without making someone else worse off.
  - **Global optimal allocation (GOA):** The maximum allocation, it is when everyone has that they want.

From IOA to BOA the following assumptions should be applied [69]:

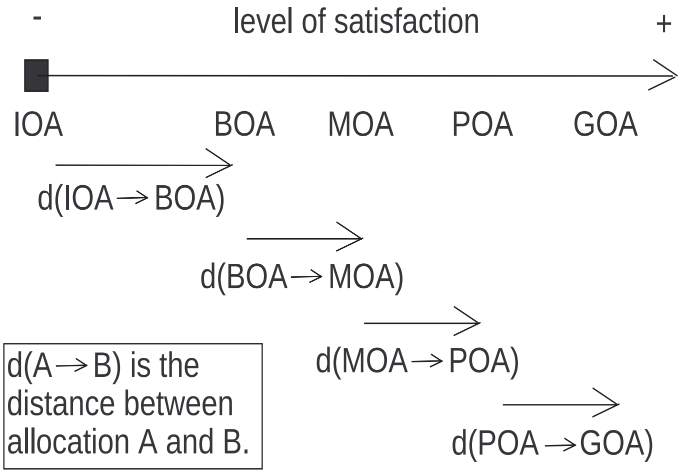


Figure 2.3: Ordered sequence of allocations.

- A rotating trading pattern: which forces every pair to trade periodically.
- Strictly convex preferences.

- **Optimal:** The first step of inquiry, we concentrate on the simple housing market introduced by Shapley and Scarf [153] and [167]. This simple environment describes pure barter of indivisible items yet important issues concerning efficiency, envy and decentralization can be analysed. At each period, a pair of traders is matched randomly and they trade their endowments if and only if trade is mutually beneficial therefore, myopia is a component of their behaviour. See [71], [118], [152], [168].

  The performance in pair–wise exchange–based is limited in systems with large populations and great diversity of interest, for it is relatively rare to match users in pairs. Furthermore, primitive pair–wise exchange schemes with the simple tit–for–tat strategy, also perform unsatisfactorily, due to the difficulty for the serving participant to predict which other participant it is serving who may serve its in the future. In order to increase the possible exchanges a way is to increase the number of participants. For example, the natural extension from 2–way exchange is the 3–way exchange, 3–way exchange–based scheme enlarges the matching possibility by introducing 3 participant exchanges. The main task in the 3–way schemes is to realize feasible exchanges with 3 participants. On the other hand, this new approach is adding complexity in the exchange protocol. The original requester C selects a node S from the query results for downloading the entries. Due to potentially large traffic, C and S make a direct connection to retrieve entries rather than communicating through a chain of neighbours. However, S has no incentive to upload entries to C as it only costs S its resources. Thus, C needs to find either an altruistic S that unconditionally uploads to C or a circular dependency of requests. For example, if S also wants to download some other entries from C, S and C form a circular dependency of length 2. Or if there exists a node P such that P wants to download from C, and S from P, they form a circular dependency of length 3. If a circular dependency is found, they are likely to agree to serving one in exchange of being served by another.

If a cycle is established, then all the nodes in the cycle would simultaneously participate, leading to higher utilization. In this way, the N–way scheme can improves effectiveness but comes at the expense of the prohibitive discovery procedure. However, to make 3–way or more exchanges is more difficult to achieve than 2–way exchange.

Maximal two–way exchanges are found through different versions of the algorithm of J. Edmonds (see [43], [61]), as discussed in Roth et al. [155] maximal two–way, three–way and maximal unrestricted exchanges are found through various formulations of the exchange problem as an integer programming problem. The ability to perform three–way or more exchanges has been demonstrated by increasing the number of possible exchanges that can be identified. See [54], [69], [80], [109].

- **Bartering strategies:** In a bartering economy, each agent relationship can be viewed as an instance of an Iterated Prisoner's Dilemma (IPD). In each round, agents play part of the Prisoner's Dilemma. Let R_{local} denote the value of local resources and R_{remote} the value of remote resources. The reward R for cooperation for both traders is thus $R_{remote} - R_{local}$. The punishment M for mutual defection is zero. Finally, the temptation to detect T and the sucker's payoff S are R_{remote} and $-R_{local}$, respectively. Hence, we have the necessary conditions for a Prisoner's Dilemma: T>R>M>S.

  Since users are considered to be *self–interested* rather than malicious, the best way to discourage defections is to offer an alternative that gives them better performance at a lower cost. It is useful for the system as a whole, and respects their desire.

- **Centralized versus distributed allocations:**

- In the centralized case, a single entity decides on the final allocation, possibly after having elicited the preferences of the other agents.
- In the distributed case, allocations emerge as the result of a sequence of local negotiation steps. Such local steps may or may not be subjected to restrictions such as:
    - **Structural:** bilateral deal, topology
    - **Informational:** open, restricted
    - **Behavioural:** selfish, malicious, altruist

Unfortunately, these factors make it difficult to reach the optimal allocation (GOA) in the distributed approach (see Figure 2.4). Since the agents do not wish to disclose all their information, for example, other agents need to base their decisions on incomplete information. The situation is even more complex when agents are competitive because agents will be inclined to make selfish decisions, rather than doing what is better for the group.

The centralized approach is applicable to problems in which global information is available and agents are cooperative. Problems in which some agents want to keep their information private for competitive or other reasons call for distributed methods ranging from coordination amongst cooperative agents (Durfee et al. [59]) to negotiation amongst competitive agents (Sandholm [159]).

The distributed model seems also more natural in cases where finding optimal allocations may be (computationally) infeasible, but even small improvements over the initial allocation of resources would be considered a success.

Decentralization comprises constraints on the distribution of information and authority among participants in a distributed system. In a decentralized system, the information state of an individual is considered private, and is disseminated only by voluntary communication acts. This contrasts with centralized systems, in which it is generally assumed that a single entity can obtain knowledge of the entire information state, for example by compelling communication. Decentralization constraints clearly restrict the computations performed by individual participants, and apparently of the system as a whole.

Because computational environments are increasingly decentralized in some respects (e.g., Multi–Agent Systems, where agents represent distinct individuals or organizations with diverse information and inter-

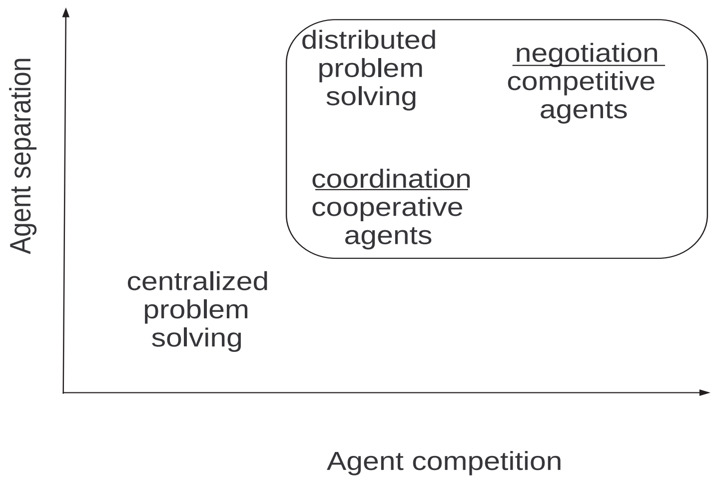


Figure 2.4: Approaches relating to the problem space.

ests), it is important to understand the computational properties of decentralized systems.

- **Myopic or non–fully vision:** Agents may not know all the state of the system such as preferences and ownership of the rest of the population. When the preferences are not common knowledge, self–interested agents often fail to explore win–win possibilities. A mechanism to overcome the informational restrictions is to add a list of preferences and ownership for each agent in the environment. Even the result of the allocation we could assume non–malicious agents when they are providing their preferences. Indeed, non–rational trades should be accepted even when the agents have all information to reach the GOA.

- **Emergent computation:** Many systems in nature exhibit sophisticated collective information-processing abilities that emerge from the individual actions of simple components interacting via restricted communication pathways. Some often cited examples include efficient foraging and intricate nest-building in insect societies (1), the spontaneous aggregation of a reproductive multicellular organism from individual amoeba in the life cycle of the Dictyostelium slime mold (2), the parallel and distributed processing of sensory information by assemblies of neurons in the brain (3), and the optimal pricing of goods in an economy arising from agents obeying local rules of commerce (4). Allowing global coordination to emerge from a decentralized collection of simple components has important advantages over explicit central control in both natural and human constructed information-processing systems. There are substantial costs incurred in having centralized coordination, not the least being (i) speed (i.e. a central coordinator can be a bottleneck to fast information processing), (ii) robustness (i.e. if the central coordinator is injured or lost, the entire system collapses), and (iii) equitable resource allocation.

The value of an information sharing community is often directly proportional to the size of the community: larger communities may provide more information to the individual users and so provide greater value. As communities grow, however, locating information becomes a critical challenge. A resource location operation, to find out who owns the item they need, is required in a bartering market. See [51], [198].

- **Replication and non–replication:** In *information diffusion* the non–rivalry property is commonly assumed. In contrast, in our approach items only belong to an unique member in the social network at the same time. For this reason, when items change hands, the owner of these items loses the utility/*los* associated with the items and this does not happen in the information diffusion approach.[186]

2.3 Summary

This chapter outlines the features that exhibit the bartering model. The rest of the thesis uses the bartering model focusing on different elements of bartering.

- General Framework and Simulation chapter sets the guidelines for the next three chapters.
- Bartering Networks chapter is focused on network structure challenge.
- Trading Paperclips chapter is focused on individual interest challenge.
- Distributed Barter–Based Directory Services chapter is focused on detection of needs and network structure challenges.

Chapter 3

Methodology

In this chapter, the methodology followed during the production of this thesis is discussed. This work applies a *general model* which establishes base rules applicable to a wide range of bartering situations. Starting with a common model brings several advantages such as focusing on a common purpose, avoids irrelevant issues, and allows us to reach an agreement about the rules used in concrete models. Once the base rules are known, the next task is to customise this general model into a concrete one. Then looking at the general model, the types of issues to be considered in such bartering worlds included:

- What is the loss between bilateral allocation and Pareto optimal allocation? (i.e. the loss in allocation efficiency and is there indeed a loss?)
- What is the price to be paid for dealing with selfish agents in distributed environments, versus altruistic agents?
- What conditions are necessary in a market to ensure that a decision–maker will turn up a non–valuable item into a valuable item?
- How many decision–makers following the same pattern can achieve such an objective?
- Can the use of bartering be applicable in a real scenario? Is it useful?
- How does the request distribution affect the stability of the knowledge acquired during the bartering process? and, if so, how?

Checking relevant examples and simulations allows us to derive results relevant to the efficiency and efficacy of bartering environments. Figure 3.1 sketches this methodology chapter.

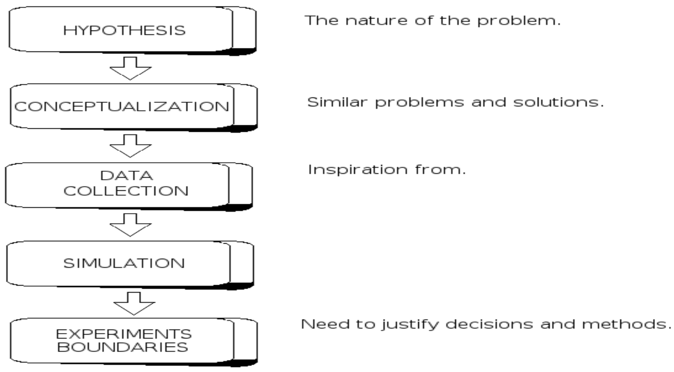


Figure 3.1: Methodology structure.

The experimental settings are centred on evaluation of the results – positive or negative evidence from the following scenarios:

1. Investigation of the general features of bartering environments and on the study of performance of exchanges from two–way to tree–way exchanges.

2. Analysis of how applying beneficial exchange to get valuable goods and the replication of patterns.

3. Provides in a competitive environment access to information in a directory. This is a validation of a specific application.

3.1 Conceptualisation

Conceptualisation refers to deliberate analysis beyond the known i.e., beyond beliefs, assumptions, commonplace interpretations, prevailing theories, habitual conclusions and so on to see what is not yet known. The inspiration for our work comes from many places, but the heart of our design is always driven by the main goal, to explore and analyse bartering in the Internet Age. This section shows way to analyse complex distributed systems that match with our vision of the world.

Most modern computing systems are distributed: large collections of interconnected components whose interactions lead to macroscopic behaviours. A common property of these systems is that they are extremely complex to design, debug, and maintain. The other main challenge is the *autonomy of the participants* in the environment. Without a centralised control, the power is distributed amongst the participants and this entails important changes with respect to a centralised solution.

One vision of this world is *agent–based modelling*. The first advantage of agent based modelling is its capability to show how collective phenomena came about and how the interaction of the autonomous and heterogeneous agents leads to the genesis of these phenomena. Furthermore, agent-based modelling aims at the isolation of critical behaviour in order to identify individual agents that more than others, driving the collective results of the system.

The second advantage of agent–based modelling, which is complementary to the first one, is a more normative one. Agent–based models are not only used to get a deeper understanding of the inherent forces that drive a system and influence the characteristics of a system. Agent–based modellers use their models as computational laboratories to explore various institutional arrangements, various potential paths of development so as to assist and guide e.g. firms, policy makers etc. in their particular decision context.

Agent–based modelling uses methods and insights from diverse disciplines such as evolutionary economics, cognitive science and computer science in its attempt to model the bottom-up emergence of phenomena and the top–down influence of the collective phenomena on individual behaviour.[19]

Building on the work by Schelling, Epstein and Axtell [66], who used agent–based computational experiments to investigate how various collective behaviours might arise from the interactions of agents following simple rules of behaviour [151], with respect to the relevance of the market structure, Wilhite [192] uses a model of a bilateral exchange economy to explore the consequences of restricting trade to small–world trade networks.[189]

The method of agent–based computational economics can be summarised as below [179], [178]:

- Firstly research defines the problem to resolve.
- The researcher then constructs a virtual economic world with groups of agents.
- The modeller sets initial conditions of the world, cf. the trading rules of the world, the attributes and learning model of the agents, what are the preconditions of the experiment.
- The modeller then lets the world evolve over time without further outside intervention.
- Finally the researcher analyses and attempts to explain the data generated according to economic principles or proposes policy suggestions

to guide practices.

A different vision comes from *methodological individualism* [13]. Methodological individualism is a philosophical method aimed at explaining and understanding broad society–wide developments as the aggregation of decisions by individuals. This theory is an essential part of modern neoclassical economics, which usually analyses collective action in terms of *rational*, utility–maximising individuals. This is the so called Homo–economicus postulate. In this view, the structure and dynamics of most economic institutions can be analysed.

Cognitive economics [28] has emerged in recent decades as the study of economic systems based on the cognitive capacities and processes of the participating social agents in social networks, their knowledge, beliefs, desires and intentions. Cognitive economics studies:

- The processes of individual and collective decision-making and reasoning, distributed problem solving and individual and organisational learning;
- The social interactions between economic agents and their co-operation, co-ordination, and competition;
- The role and emergence of norms and other institutions, the influence of different norms (in particular market rules) on individual behaviour and collective outcome;
- The evolution of rules, norms, and institutions and the processes of self–organisation of societies.

The *P2P paradigm* exhibits three characteristics related to this thesis: self–organisation, symmetric communication and distributed control.[157] The difficulty of finding, retrieving and using network resources (i.e. content, services, or hardware), increases with network size and degree of decentralisation. The problems that can be solved with proposed P2P approaches, amongst others, are data sharing and dissemination as well as distributed system control.[125]

Further, many P2P research efforts are centred on the key issue of altruism versus selfish behaviour in peer networks – targeting specifically how to avoid misbehaviour and non–desired behaviour. See [144], [187].

Researchers in economics have turned also to the modelling of artificial economies using, in many cases, Multi–Agent Systems (MAS) like paradigm as a powerful approach to be applied to problems involving complex dynamics such as evolving systems of autonomous interacting agents [182], firm formation [17] and consumer behaviour [5]. Software-based agents systems try to solve complex tasks by using a set of autonomous agents. Once the word software is removed, there are many similarities between multi–agent systems and societies of humans. Multi Agent–Based Simulation (MABS) is an intensive field of research for example in computer science, social science, mathematics or economics. The study of economic systems with MABS have become known as Agent-based Computational Economics (ACE). Economies are modelled as independent evolving systems of autonomous interacting intelligent agents. The goal of market simulations is to assess the market behaviour and its development over time. Agents applied in simulations normally use simple decision rules, learning algorithms, or statistical analysis to adapt their strategies. Tesfatsion [180] provides a detailed overview on ACE research and describes studies of market simulations in electricity and financial markets.

This thesis spans a wide range of research areas, such as economy, agents and P2P systems. Therefore, the methodology used also takes into account existing methodologies of these three areas.

3.2 Data Collection

Within the thesis work, three techniques of data collection have been used:

- **Experiments**: An experiment focuses on investigating a few variables and the ways in which these are affected by the experimental conditions. Typically, experiments are used to verify or falsify a previously formulated hypothesis.

- **Case Study**: A case study project is undertaken as an in-depth exploration of a phenomenon in its natural setting. A characteristic of a case study is that it involves a limited number of cases, sometimes even a single case. This allows to undertake a detailed examination of the phenomenon.

- **Application**: Many projects in computer science and information systems consist of developing new solutions. Such a solution can consist of a new software architecture, method, procedure, algorithm, or some other technique, which solves some problem in a new way, which has some advantage over existing solutions. In a project of this type, it is often necessary to implement the proposed solution, in order to demonstrate that it really does possess the proposed advantages. The goal of the application, then, is to demonstrate that the solution has certain properties/conditions it behaves in a specific way. This application often needs to be compared with applications of existing solutions, before conclusions can be drawn.

The experiments are applied in the Bartering Network, Trading Paperclips and Distributed Barter–Based Directory Services (DBBDS), case study technique was applied in Trading Paperclips and lastly, the application technique for Distributed Barter–Based Directory Services.

3.3 Simulation

Multi–Agent Simulation was selected as the chosen approach within the thesis, given its strong suitability for the exploration of resource allocation in economics research (see the section above on Conceptualisation).

The model in this thesis assumes a large population of n peers joining a network. We examine the behaviour of autonomous and rational peers who maximise their utility within a fixed time period, considered as a time unit. Each peer acts as a strategic player, whose decision variable is the level of his contribution, ranging from zero to a maximum quantity, that reflects any constraints on content availability. All peers act simultaneously during a time period and the only way to exchange is by means of bartering. At each exchange the agents only wants to improve its utility/satisfaction. At the end of a time period, each peer realises its total payoff.

The experiments in the scenarios cover a wide range of parameters. However, each scenario is focused on showing different sides of bartering. For example, Bartering Networks is related to efficient and conditions in the bartering exchange. Trading Paperclips estimates the conditions in the market and the percentage of agents that can obtain a valuable item. Finally, Distributed Barter–Based Directory Services is focuses on query behaviour. For this reason, the parameters depends on the features of each scenario.

3.4 Experimental Boundaries

The world modelled in this thesis is composed of interconnected decision–makers. The only available way to negotiate within the environment is using bartering. As a network, the topology and information is a relevant feature in the model. In Figure 6.7 topologies with a wide range of links are shown: from fully–connected to sparse–connected topologies. Figure 8.5 shows two topologies: Erdos–Renyi and random structure. These structures allow the study of the relevance of quantity of links in direct exchange scenarios. The quantity of participants in the models ranges from 500 nodes in Bartering Networks, 5,000 nodes in Trading Paperclips and 100 nodes in DBBDS. Another feature is the behaviour of the agents. Assuming that any decision is always taken for its own benefit, two behaviours are modelled – active and passive: active is when the agent is looking for a trade and passive is when the agent is expecting a trade proposal.

In general terms, the boundaries for the experiments have these values. All of them follow a similar approach because all of them start from a common model but each one has some variations in the parameters.

3.5 Summary

The study of dynamics of social networks in distributed environments such as MAS and P2P can help us to understand the allocation of content or resources. One has to consider underlying social beliefs and desires, whose connectivity and topology play important roles in mediating agent–agent or peer-peer interactions.

We are interested in selfish communities, or in other words, communities that do not presume altruism in their members. The reason for this is that in open environments with autonomous and rational peers/agents who want maximise their utility, to assume this type of behaviour can not be considered a reasonable condition.

Experiments focus on investigating a limited number of variables and the ways in which these are affected by the experimental conditions starting from a general model. The next task was to fine tune this general model and run simulations to see how each one of the concrete models were affected by different variables.

Our point of departure in agent–based modelling is the individual: We gave agents rules of behaviour and then move the system forward in time and see what the performance and the content distribution and re–allocation changes that emerges together with their features and properties.

Following the method proposed by agent–based computational economics in this thesis, the problem definition and construction of the virtual economic world is depicted in General Framework and Simulation chapter. Initial conditions, developing the environments and evaluating the results are shown in the Bartering Networks, Trading Paperclips and Distributed Barter–Based Directory Services chapters.

Chapter 4

Related Work

This chapter summarizes existing work, particularly in the fields of economic theory, Multi–Agent Systems (MAS) and Peer–to–Peer (P2P) from the sciences that have the which are of relevance to our work. The thesis is focused on three scenarios. Each of these scenarios are interconnected, but there are appreciate subtle differences between the related work for each of one of these scenarios. To further this end this chapter discusses relevant research fields which is followed by a related fields section for each scenario. But firstly a wide range of examples and fields where bartering is present together with a P2P example are disclosed:

- An art student, Lina Fenequito, created an interactive vending machine placed in public places such as bars and cafes and where different kinds of artefact could be swapped for others by the users. As Fenequito comments on her website: "The Swap–O–Matic[1] will attempt to promote the recycling of objects through the interface of a vending machine, which features used rather than new products. Participation with the system will allow users to rethink spending patterns, view consumption with a different perspective, and explore issues of material possessions and American consumption through a public installation. The Swap–O–Matic is intended to be both a solution and critical response to the gluttonous culture that we live in today. Its core function is to support the reuse and recycling of consumer products through swapping among participants."

- The BitTorrent protocol a P2P file–sharing that has attracted millions of users and uses a bartering technique for downloading in order to prevent users from free–riding.

[1]Swap–O–Matic in www.swap-o-matic.com

These two examples show the wide range of scenarios where bartering is applicable. Therefore, this involves a variety of related fields studied in this chapter.

4.1 Research Fields

Three research fields are very related with to research of this thesis. Obviously, the economic and bartering theory perse. In many cases the complexity of the economic situation was explained by the interaction of simple participants, mainly behaving in a structured environment. The scarce of resources is lead using economic approaches. Other area is agent–based model, the agent–based modelling allows to model the bottom–up emergence of phenomena and the top down influence of the collective phenomena on individual behaviour. The last research that is useful for the work is P2P computing. P2P devised solutions to problems that appear again in our model. In this section the links between the related research fields are discussed.

Economic and bartering theory: Decentralized market economies are complex adaptive systems, consisting of large numbers of adaptive agents involved in parallel local interactions. These local interactions give rise to macroeconomic regularities such as shared market protocols and behavioural norms which in turn feed back into the determination of local interactions. The result is a complicated dynamic system of recurrent causal chains connecting individual behaviours, interaction networks, and social welfare outcomes. To build an agent–based world capturing key aspects of a decentralized market economy, introducing self–interested trades and observing the degree of coordination that results from the interaction of its participants.

Multi–Agent System: Agent–based models or agent simulations are a powerful methodology to gain insight into these complex systems. Thus, agent models can provide results and findings that can help to better understand complex social processes that take place in society. The first advantage of agent based modelling is their capability to show how collective phenomena came about and how the interaction of the autonomous and heterogeneous agents leads to the genesis of these phenomena. The second advantage is it flexibility.[66]

P2P: Direct exchange of resources is the simplest to implement incentive mechanism. It is enforced by definition and is totally memory-less and anonymous. For example, BitTorrent [42]. BitTorrent is an example of a real world application focusing on bandwidth provisioning for content distribution, which actually implements a reciprocative incentive scheme without relying on past transactions of peers but on a direct exchange of resources.

Because the incentive scheme does not rely on tracking the long term behaviour of peers it is simple to implement and largely immune to problems of false trading and whitewashing. Also notice that direct exchange is a natural mechanism used in other areas such as in preservation systems [44] and P2P multicast streaming.[94]

4.2 Related Fields

This section compares the subject matter of in this thesis with other related works. Showing the relevance of this work with respect to previous work made in similar research.

Bartering Networks: We assume that agents aim to optimize their exchanges in terms of these goals under imperfect, local information without initial knowledge about others' characteristics or knowledge about the global network structure [92]. As we will show, these assumptions do not preclude the emergence of complex networks. These assumptions, in a greater or lesser degree, have been touched in previous papers as:

Contract Types for Satisfying Task Allocation: I Theoretical Results [159] and Contract Types for Satisfying Task Allocation: II Experimental Results [8] review different types of contract, analysed them and experimented with.

Bilateral Trading Processes, pairwise Optimality, and Pareto Optimality [69] studies the bilateral trading process, showing that under certain conditions a sequence of bilateral trades will carry the economy to a pairwise optimal allocation.

On the Communication Complexity of Multilateral Trading [64] is deployed a negotiation framework which makes multilateral deals a necessity; this is the price to pay for the simplicity of our agent model based on the notion of rationality. If agents only agree to deal with something that improves their own welfare (i.e. rather than being prepared to accept a temporary loss in utility in view of potential future rewards), then deals involving any number of agents as well as resources may require to be able to guarantee socially optimal outcomes.

Bartering Leftovers on the Internet [196] proposes a centralized algorithm for finding maximal sequence of exchanges which is implemented only as an advise for the users in the system. Because it is assumed that users will frequently tend to not follow the solution suggested by the algorithm. The protocol is designed to allow negotiations between the users before they agree with a proposed exchange. Negotiations allow users to choose the next exchange using updated information about the preferences and modified offers of relevant users.

Inefficiencies in Task allocation for Multi–Agent Planning with Bilateral Deals [54] explains that without recontracting and multilateral deals the allocation problem can be inefficient. Recent studies show that under certain assumptions simply allowing recontracting can lead to repeat cycles of making and breaking contracts. However, there are protocols that prevent such deadlock situations. For example, the levelled commitment protocol introduces penalties for breaking contracts (Sandholm & Lesser 2001).[161]

How to exchange Items [162] shows that for a given system there always exists a unique stable re–allocation, and presents a simple and fast algorithm to find it from the revealed lists.

On Optimal Outcomes of Negotiations over Resources [65] are studied conditions to obtain optimal outcomes.

On Cooperative Content Distribution and the Price of Barter [76] is developed a barter–like mechanisms and explores the three–way trade–off between the mechanisms enforceability, their ability to incentive uploads, and the efficiency of content distribution. To this end, they are considered three different mechanisms based on barter, informally analyse their incentive structure, derive lower bounds and develop actual algorithms for content distribution.

In Monotonic Concession Protocol [63] is explained the Monotonic Concession Protocol (MCP) process. The MCP is a bilateral bargaining process. The process begins by requesting all interested suppliers to propose a deal simultaneously in the first round. The contractor and suppliers will then make a concession alternatively until an agreement is reached. If neither the contractor nor suppliers make a concession in the same round, then negotiation terminates with a conflicting deal. The disadvantage of MCP is the uncertainty associated with the bargaining process at termination, as a party cannot identify the environment and opponents accurately.

The problem of optimally allocating data objects given space constraints is well known in computer science. Distributed bin packing problems [122] and the File allocation Problem [38] are known to be NP–hard.

Anagnostakis and Greenwald [7] propose exchange based mechanisms for providing incentives for cooperation. This approach is generalized to n-wise exchanges among rings of peers and a search algorithm for locating such rings is presented. For its part, the work from Özturan [136], Roth [154] have revealed the importance in the market performance with respect to the individuals that involves a bartering arrangement.[155]

In our case, we have focused on requirements of barter environments and performance in two [69] and three way exchanges comparing these results with respect to Kuhn–Munkres algorithm that resolves the optimal assignment problem and maximal two–way exchanges from the algorithm of J. Edmonds. Developing infrastructure to perform three–way as well as two-way exchanges will have a substantial effect on the number of exchanges that can be arranged. And computing not only the actual maximal number of exchanges, but also the predicted number based on the formulas derived above.

Exchange–based mechanisms are also discussed in [49] for incentivizing users of peer–to–peer storage systems to contribute resources. The work most closely related to ours is BitTorrent, a system for large–scale content distribution where peers exchange blocks of the same file in an effort to expedite the distribution of large files [42]. The approach is more limited in that it only supports two–way exchanges on the same file, and appears to be vulnerable to free–riding middlemen. To the best of our knowledge, our study is the first to examine the effect of exchange mechanisms on peer performance and their value as an incentive mechanism in a file–sharing system. Systems such as Scrivener [128] adopt a more advanced content trading mechanism called transitive trade. Transitive trade establishes a credit path from the requesting node to the node that has the desired file. Credits are then transferred along this path and the download may start. Discovering credit paths is, however, a complex problem, and there is always a chance that no path exists between two particular peers.

Trading Paperclips: The increasing popularity of P2P networks and other such forms of distribution networks, has made the bartering model increasingly relevant to the modern technological world. See [29], [81], [150], [1]. Examples are present in many different areas such as file sharing [7], query forwarding [31], routing [23], knowledge diffusion [47], storage–sharing systems [46], and WIFI hotspot sharing [62]. Barter has also been used in B2B commerce with many others examples such as BizXchange, ITEX, BarterCard, SwapAce and Worldwide Barter Board or SwapTree and Continental Trade Exchange. Barter mechanisms are therefore of significant interest in the Internet Age.

Trading Paperclips scenario is a classic example of bartering and arbitrage [55] – where value is extracted by playing on the asymmetries of users valuations. Betting exchanges have many similarities to the Kyle's experiment. Betfair[2], Betdaq[3] and other similar betting exchanges have a huge turn over now, and many billions of pounds are gambled each month on these markets. In betting exchanges an arbitrageur exploits existing price discrepancies when bookmakers' prices differ enough that they allow the backing of all outcomes and still make a profit. In paperclip exchanges, Kyle exploits personal values discrepancies. Both Kyle and sports betting take advantage

[2]Betfair in http://www.betfair.com

[3]Betdaq in http://www.betdaq.com

of the personal valuation differential between agents in large–scale markets. But there are still barriers which stop everyone from being successful in both scenarios. Both scenarios require capital, time, organization and energy, to make profits.

More research is needed on analysing the global behaviour of a system based on individual negotiations/exchanges between agents[4] ([130], [99], [91]). To predict the overall behaviour that emerges as a result of interaction agents we have proposed an economic model, which provides a variety of real economy features and we use simulations to show their performance. Also this scenario touches approaches from different methods and features such as:

- **Path–finding**: Path–finding is a term used mostly by computer applications to plot the best route from point A to point B. In the Trading Paperclips, point A is the start range and point B is the last range.
- **Limited backtracking**: Backtracking algorithm is a method of solving problems automatically by a systematic search of the possible solutions. Limited backtracking is not an exhaustive search.
- **Competitive search**: It relies crucially on the assumption of a competitive environment where each trader decides whether to trade up and each trace has influences on environment.

In a telecommunications network, a call between two parties may be connected via one of a number of paths. The process of deciding which of these paths to use is called routing. Choosing an efficient path is important because the networks capacity for handling traffic is finite, and when it is saturated, calls have to be turned away. This constitutes a loss of income to the network provider. However, finding the optimal path is problematic because the network state continually evolves. By the time the information needed to compute the optimal path between any two nodes is made available at the node where that decision needs to be taken, the network state will probably have changed, rendering that decision obsolete. Furthermore, efficient routing decisions, those which maintain a balance in utilization of the network resources, require information about the utilization of all network resources to be made simultaneously available to the process making that decision.

Distributed Barter–Based Directory Services (DBBDS): Domain Name System (DNS), probably the best and widely known of directory service, has some alternatives in looking for distributed systems ([145], [50])

[4] For example, the Mancur Olson conjecture that larger groups encourage free riding and lead to lower supply has been confirmed.

revealing pros and cons to turn a centralized directory service into a distributed one. Community–based replication has connections with *DBBDS*. In these communities multiple archives cooperate to preserve data. Each site contributes storage resources to the system, and in return reserves the right to store copies of its own collection at other sites. A community–based replication system is subject to two constraints:

- Each site is autonomous.
- Each site has limited resources.

Because each site wants to make its own decisions about how to allocate its sparse resources, it is not feasible to have a central authority dictate which copies will be stored at which sites. Such a central authority is not desirable in any case, since the system is more robust if allocations can be made in a distributed manner. To overcome these constraints, [27] et al. have designed a framework for negotiations between sites to allocate resources. The basis of these negotiations is a trade, where one site essentially says to another: "I will store a copy of your data if you will store a copy of mine." If both sites agree to this proposition, then they conclude an agreement and allocate space for each others use. This distributed, barter–based negotiation allows each site to decide what agreements to conclude and thus how to use its own resources. Moreover, they can study policies for deciding when to make trades that allow a site to make the most of its limited resources . In turn Cooper et al. [46] propose a bartering storage system for preserving information. Institutions which have common requirements and storage infrastructure can use the framework to barter with each other for storage services.

The major drawback of existing large scale content distribution systems is the directory service, which generally consists on an index server and a tracker server. The index server (e.g., a web server) hosts all the metadata of shared content. In effect, such a directory service does not scale well as it cannot accommodate a large number of requests when the population of the system increases rapidly. In order to overcome this problem, many systems propose a decentralized service directory infrastructure ([50], [57]) such as Novell's NDS, Microsoft's Active Directory and others.

To improve the performance of large scale content systems, most of the work has been focused on keeping the cache information close to the client applications that access the directory information [41]. For example, to enhance web browsing, content distribution networks (CDNs) [174] move web content closer to clients by caching copies of web objects on thousands of servers worldwide. Additionally, to minimize client download times, such systems perform extensive network and server measurements, and use them to redirect clients to different servers over short time scales. CDNs include systems such as those provided by AKAMAI[5], Mirror Image[6], BitGravity[7], CacheFly[8], and LimeLight[9].

In general, any redundancy systems that allocate limited resources can use a trading mechanism as an infrastructure component. Some existing systems allocate redundant resources in a fixed, static way. Although it is possible to reason about good or even optimal policies for certain configurations, it is difficult to do so in a distributed system with autonomous peers. Moreover, if the configuration is highly dynamic then the fixed allocation may no longer be appropriate. In contrast, other existing distributed and Peer–to–Peer systems allocate resources in response to user demand, or even randomly. Allocating in response to user requests may mean that less popular collections are not preserved at all. Allocating randomly may make inefficient use of community resources. If the goal is to ensure redundancy and high reliability, then trading provides a way to achieve effective allocation while dynamically adapting to changes in user requirements and network configuration. See [44], [46].

A trading–based P2P system has several advantages: First, it preserves the autonomy of individual peers. Second, the symmetric nature of trading ensures fairness and discourages free–loading. Third, the system is robust in the face of failure. Because the trading network is composed of binary trading links, individual links or sites can fail without crashing the whole network. See [173], [148].

Our approach, differs from these systems in a fundamental way: these systems relies on the other participants. For example a distributed DNS requires people publishing names to rely on other people's serves to serve those names. This is a problem for many P2P systems: there is no incentive to run a P2P server rather than just use the servers run by others. In our proposal, directory systems work by following a similar idea but applying a bartering mechanism. See [111], [1]. The providers of entries want to have, or to have near, the content most requested by their clients, this proximity is achieved by exchanging entries with neighbours that follow the same strategy. Each self–interested provider/trader starts with some given initial bundle of entries. A new set of required entries, is build up from the clients queries. The providers discuss the proposal distribution among themselves taking the best choice for its clients (i.e. trying to get the most requested entries by

[5]AKAMAI in www.akamai.com
[6]Mirror Image in www.mirror-image.com
[7]BitGravity in www.bitGravity.com
[8]CacheFly in www.cachefly.com
[9]LimeLight in www.limelight.com

its clients). If a provider/buyer decides that it can do better on its own, with its given initial entries, it makes a proposal of exchange that the other provider/seller should evaluate and this proposal only will be accepted if it is beneficial. When both parties accept the exchange, entries are transferred between them.[102]

4.3 Summary

To conclude, this chapter shows the state of the art in bartering, mainly from the fields of economics, agents and P2P systems. This thesis combines techniques from these three areas.

PART 2: Innovation and Execution

Chapter 5

General Framework and Simulation

This chapter provides an overview of the topic of concern of the thesis and will be used as a foundation for the next three chapters: *Bartering Networks*, *Trading Paperclips* and *Distributed Barter-Based Directory Services*. Each of these chapters cover theoretical, experimental and practical bartering issues respectively, starting from the common point of view depicted in this chapter:

- *Bartering Networks* is the most theoretical vision of bartering. This scenario is focused on *optimal assignment*, the distribution of a set of items amongst a set of distributed and autonomous agents, with varying preferences.
- *Trading Paperclips* shows bartering dynamics in an open bartering environment by means of simulations. This scenario is focused on *social mobility*, the degree to which goal–driven individual's or groups move up and down the value system playing on the asymmetries valuations.
- The *Distributed Barter–Based Directory Services* chapter is a practical example of bartering used in an application. This scenario is focused on the *distributed directory services*, the problem to solve is to repeatedly allocate a set of entries in accordance with clients demands at successive points in time. The basic model behind this service involves partial customer preferences over entries, and where the directory services aims is to satisfy these preferences as fast as possible.

The heart of the matter in all cases is to investigate interactions amongst *selfish*, *rational*, and *autonomous* agents [169] each one with *incomplete information*, and each seeking to *maximize* its expected utility by means of exchanges. Therefore, the general scenario addressed is:

- A population of distributed agents with randomly distributed content,
- Local interactions give rise to global regularities.
- Global regularities feed back into local interactions.
- Taking into account the fact that different agents have content which others may want and viceversa,
- A market is used as an incentive mechanism to help the agents to *organize* themselves in the sense that they reorganize the location of the content to improve their levels of satisfaction.
- Taking into account the combination of factors which include the private and limited nature of the information together with the inherent rivalry of agents which together restrict trade opportunities.[79]
- Where the trade mechanism used is bartering.

In the following chapters, a *distributed, open and large–scale environment* where *self–interested agents* try to get its *optimal satisfaction* is considered, but this chapter is the starting point of all the research undertaken during this thesis. For this reason, the general model is explained in detail in the rest of the sections of this chapter. The next section provides the details necessary to understand the common frame–based bartering approach. This is followed by the key integrating section setting out our methodology and detailing how it might deployed.[98]

5.1 Model Description

Our discussion is based on the assumption that each participant within the market environment is separate and modelled as an individual entity, that is networked with other individual participants. The allocations made are the result of interactions between various participants, interactions that are guided by local and selfish decisions and these allocations could only be done by means of exchange between participants.

The details of our general model are as follows:

- Initially, items are randomly assigned to agents.
- The market studied is composed of agents (nodes) which desire items.
- Nodes are located in a network and are linked to a small quantity of other nodes.

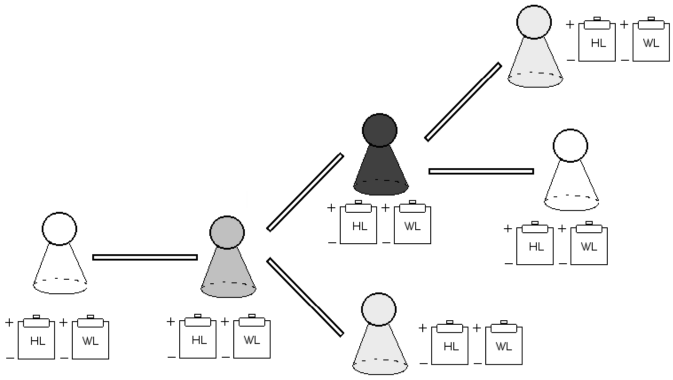


Figure 5.1: Skeleton of the general framework.

- The links amongst nodes are static, but the nodes that form the network have periods of being switched on and off.
- Each item has a unique level of satisfaction associated with it for each agent in the system (level of satisfaction – *los*). The *los* provides from the items that an agent has.
- Trades are conducted by means of currency or bartering.
- Trades modify the global *los*.
- Members take only local decisions.
- Information about available items is only available from local connections.
- Members can only trade with directly connected neighbours.
- Members only decide to trade when the trade is immediately beneficial.
- Global performance is measured as the sum of *los* over all agents.
- A steady state is achieved when no more trades are possible.

Figure 5.1 shows a skeleton with the common elements that composes a *Bartering Networks*. The network has autonomous and self–interested participants. Each participant has a set of desires (i.e. want–list (WL)) and some ownerships (i.e. have–list (HL)). Participants in the market are connected to other participants, by means of these connections they can engage in trades.[162]

Models should be as simple as possible, and predict as much as possible. The elements that compose the model are:

- A list of agents: The decision–makers in the market.

- A list of items: The content with the which agents trade. In the model the assumption is made that sharing is carried out in such a way as to not violate copyright prohibitions and hence not allow copies to be generated.

- Links/Relations: Each agent is connected to a set of the members in the market with which the agent can trade.

- Social behaviour: Within behavioural finance, it is assumed that the information structure and the characteristics of market participants systematically influence individuals' investment decisions as well as market outcomes.

  - Altruistic behaviour: Agent that follows this behaviour is offering items that could implies a certain cost associated for nothing. See [139], [106].
  - Selfish behaviour: In this case, the agent only wants to increase its satisfaction.[53]

- Information: Two different kinds of information are used.

  - List of preferences (i.e. want–list (WL)): The items that the agent wants.
  - List of ownership (i.e. have–list (HL)): The items that the agent has.

  The list of ownerships values the items of an agent, and the list of preferences values the items wants. The former always contains information for the local agent only. However, the latter can be composed of local preferences or external preferences provided by neighbours in the market.

- Agent preferences: This element reflects the popularity of items in the system. Two different scenarios are analysed:

  - Heterogeneous preferences lists: In this case, agents each value items in the system independently, that is, each agent may have different preferences. For example, agent$_A$ and agent$_B$ are interested in item$_1$ and they value the item in 2,000.

- Homogeneous preferences lists: In this case, agents have the same valuations for each item as other agents do that is, all agents value each item in the same way. For example, $agent_A$ and $agent_B$ are interested in $item_1$. In this case, $agent_A$ values $item_1$ in 2,000, and for the $agent_B$ the same item has a value of 3,000.

- Content distribution: At the initial steps, each agent has assigned a randomly distributed content. By means of exchanges this distribution will be modified.

- Roles: A population of agents in which each agent plays one of these two roles:
  - Goal driven agent (GDA): These agents are looking for rich/beneficial trading encounters in order to move upwards in market value.
  - Passive agent (PA): These agents have an item and do not seek any new concrete item, however they know a good deal when they see one.

- Forms of trade:
  - Bartering: To trade content with the exchange of content. In this case, a trade is carried out, if, and only if, $agent_a$ wants content from $agent_b$ and viceversa. Furthermore, each agent must improve its own satisfaction with the trade (in some variants trades may be allowed if there is no decrease in value). With $agent_x$ with $item_2$ and $agent_y$ with $item_1$. See Eq. 5.1.

$$\{PV_x(item_1) \geq PV_x(item_2) and PV_y(item_2) \geq PV_y(item_1)\}. \tag{5.1}$$

  - Currency: To trade content with the exchange of tokens. In this case, a trade is achieved, if and only if, $agent_a$ wants content from $agent_b$, $agent_a$ has tokens to buy the content and $agent_b$ is interested in selling the item.
    * Rule 1: An agent a_b will never buy an item f, if a_b is already its owner.
    * Rule 2: If something costs more tokens than an agent a_b has, a_b cannot buy it.
    * Rule 3: If an agent a_b has enough tokens or it is not interested in any content, a_b will not offer its content.

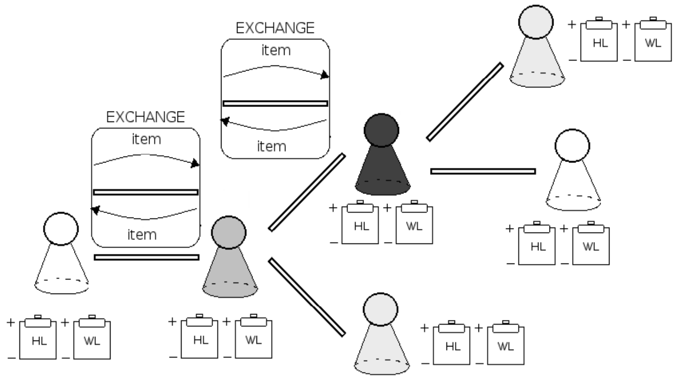


Figure 5.2: Skeleton of Bartering Network framework.

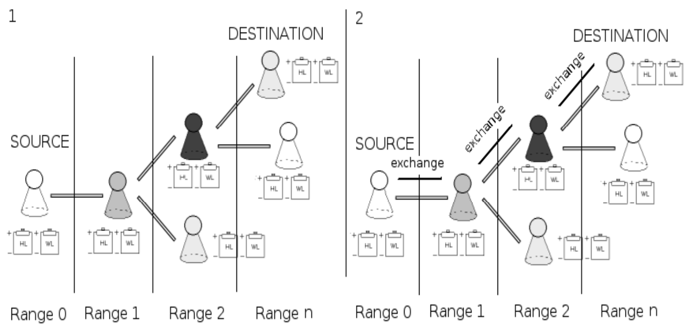


Figure 5.3: Skeleton of Trading Paperclips framework.

Mainly, the thesis is focused on scenarios with a set of agents related to agents with selfish behaviour and heterogeneous preferences list and where the form of trade is the bartering mechanism.

These common elements are the set of components used in the rest of the work; each one with their particularities, but all of them keeping the spirit of the general framework.

- *Bartering Networks:* Figure 5.2 shows the model for Bartering Networks. In this model the type of exchanges are prioritised and properties in the environment are reviewed.

- *Trading Paperclips:* Figure 5.3 shows a model for Trading Paperclips. In this model, the most relevant points are the trading–up process and the model of a list of ordered items where the agents move from a low value range to a higher one.

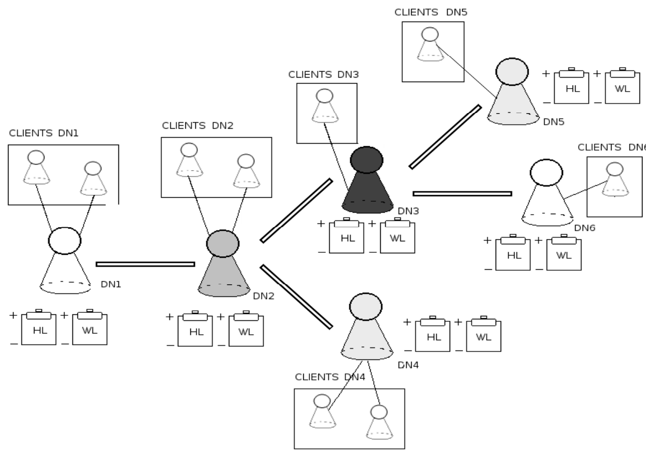


Figure 5.4: Skeleton of DBBDS framework.

- *Distributed Barter–Based Directory Services:* Figure 5.4 shows a model for Distributed Barter–Based Directory Services. In this model, relevance is defined as the query distribution from the clients.

5.2 The Environment

The environment in which bartering occurs is characterised as follows:

Distributed Environment: Matching markets where a centralised authority must find a matching between the agents on one side of the market, and the items on the other side. Such settings occur, for example, in mail–based DVD rental services such as NetFlix[1] or in some job markets. Centralised search algorithms have been known for a long time. Also, service registration and discovery are functionalities central to any service–oriented architecture, and they are often provided by centralised entities in today's systems. However, there are advantages of scalability, robustness, as well as distribution of control and cost by further decentralisation of these functionalities to all the participants in the system. However, it has a cost.[60]

Open and Large–Scale Environment: In an open environment where agents interact with each other to reach their individual goals, agents need to overcome two problems. They must be able to find each other and they must be able to interact ([89], [100]). In the model, in order to find the desired items, propagation mechanisms are used. This mechanism consist of use the neighbours information and the interactions are regulated by market policies. In a large population, agents adapt their behaviour to one another

[1] NetFlix in www.netflix.com

and their circumstances. Large–scale of population following a same pattern can show interesting dynamics in the market state.

Agents: The market is a set of agents interacting. Jennings et al. define an agent as an entity which is:

- Situated in an environment.
- Autonomous, in the sense that the system can act without direct intervention from others (humans or other software processes).
- Flexible, which is further broken down into three properties: *responsive* (perceives its environment and responds to changes in a timely fashion), *proactive* (exhibits opportunistic, goal–directed behaviour) and *social* (able to interact with humans or other artificial agents).

This definition corresponds to the capacities equip in the agents studied. The agents are situated in a market environment. Each interaction amongst the agents has an effect on the environment. Each agent in the market is an autonomous entity with its own objectives. Finally, the agents in this work follow the three properties that compose flexibility in Jennings' definition.

- *Responsive* because they take decisions depending on the information that they manage.
- *Proactive* since they are always are looking for beneficial exchanges.
- And *sociable* since the exchange process is a type of interaction.

Topology: Markets are interesting and complex exchange environments where buyers have links to multiple sellers and sellers have links to multiple buyers [110]. Users who join a network have incentives to contribute to the network, they try to use the uncertainties that exist in the exchanges within the system to their own advantage. The result is an inefficient network where the overall levels of contributions are less than would be the case if each peer acted in the interest of the entire network of peers [9]. A decentralised market structure, might be termed as a bazaar structure. In this model, all negotiation is conducted directly between peers, rather than through any centralising entity. The importance of deeply understanding of the topology of a complex network is clear. In fact, the structure heavily affects the functionality, the performance and the effectiveness of a network. See [3], [4], [96]. Initially, if all agents are free to trade with any individual in the global market, global resources are optimally allocated assuming the agents' preferences with few trades, but only after a tremendous amount of search and negotiation. If trade is restricted searches are simple but difficult to achieve. For this reason, the network that shapes the relations between agents (buyers and sellers) have a deep effect in the performance.[16]

Self–interest: Individual self–interest is the basis for the whole market system. The consumer acts according to its self–interest when it buys things at the lowest prices and with the best quality it can find. The producer acts in its self–interest in trying to make the highest profit possible. Both consumer and producer attempt to profit from their market transactions; if either side did not expect to gain, no trade would take place. This double utilisation of the profit motive efficient results. Self–interested agents, by definition, simply choose a course of action which maximises their own utility. See [10], [149], [7], [49].

Optimal: The market get an optimal state when everyone has everything that they want. The maximal two–way exchanges are found through different versions of the algorithm of J. Edmonds, as discussed in Roth et al. [154]. Maximal two-way, three-way and maximal unrestricted exchanges are found through various formulations of the exchange problem as an integer programming problem. The integer programming formulation maximises the number of exchanges subject to the constraint that the cycle size not exceed the specified exchange size (i.e. two–way, three–way, or unrestricted). Extending to maximal unrestricted exchanges or multi–way bartering is a NP–hard problem.[136]

Self–organisation: A market is perhaps the most commonly system or network, whose local dynamics profoundly affect the global system. Self–organising systems are autonomous and open, maintaining themselves through continual interaction with their environment. Similar to what occurs in a *decentralised marketplace* (see [170], [87], [77]). Market–based approaches view macro-economic phenomena as emergent results of local interactions of the economic entities [86]. Mainstream economists consider that *competition* in a market consisting of agents pursuing pure self–interest, can self–organise or reach equilibrium – a matter of faith [34]. Making the most of a free market economy as a system for allocating items in a society: supply and demand within the market determines who gets what and what is produced, rather than the central organisation. Kenneth Arrow and Gerard Debreu [14] have shown that under certain idealised conditions, a system of free trade leads to *Pareto* efficiency. The rules ordering a social self–organising system promote and reward cooperation. The rules of a self–organising market make it easier for people to enter into complex economic transactions. In a self–organising system competition grows out of the lack of perfect coordination amongst cooperative endeavours [164]. Self–organising systems are dynamic: the components are constantly changing their state to each other by means of local information (i.e. components only interact with their immediate neighbours). Some relative states are preferable for each agent, in the sense that they will be reinforced, while others are inhibited or eliminated. In markets the interactions are interchanged amongst participants. And the satisfaction entailed in each trade manages the preference of the buyers–sellers.

A society of self–interested computational agents can exhibit oscillatory or chaotic behaviour and order [183]. The initial state has a random distribution. Bilateral exchanges turn an initial and random assignation into an ordered allocation and during the order process only was taking local decisions. Studying how self–organisation emerges in terms of content distribution. A system described as self–organised is one in which elements interact in order to get a global aim. Its function is not imposed by a single element, distribution is instead achieved dynamically as the elements interact with one another by means of exchanges and each exchange is decided by an individual depending of its goals. These interactions produce feedback that endogenously regulates the system. In this case, the global aim is to get an optimal global content distribution in a file (or goods) sharing systems, search systems, and directory services systems and where the regulation is achieved by means of a market–based approach.

Generosity and altruism: Notice that, as for many P2P applications, an user valuation for the service depends on the generosity of other users: each user benefits from others' shared capacity. However, there is no direct incentive to offer one's own capacity to the others, and users are then given an incentive to free–ride. It seems reasonable to assume that each user is selfish, i.e. sensitive only to the quality of service it experiences, regardless of the effects of its actions on the other users.

There exist several intangible value generators from participating in such a system, which often involve altruism, community building, fighting the system, and more. Actually, some of these might be part of the reason why the theoretical results of economic theory are not always compatible with the performance of real P2P applications, which seems to be acceptable even without explicit incentives for cooperation. Golle et al. [81] made a first effort to model the utilities and costs associated with the participation in a P2P file sharing system. See [91], [70].

The value of the information: *Information* guides the decision–making process in order to choose the best trades. *Competition* (see [110], [192]) arises from the individual and conflicting objectives amongst the members of the market. Competition encourages buyers–sellers to compete amongst themselves in order to get the best items. This scenario is addressed in [34], [90], [193].

What is the problem we wish to solve when we try to construct a rational economic order? On certain familiar assumptions the answer is simple. If we possess all the relevant information, if we can start out from a given system of preferences and if we command complete knowledge of available means, the problem which remains is purely one of logic. The economic problem of society is a problem of the utilisation of knowledge not given to anyone in its totality [87]. Also, to add complexity at the system, agents are assumed to be self–interested. The assumption of incomplete information is intuitive because in practice, agents have private information, and for strategic reasons, they do not reveal the strategic reasons, constrains or preferences. The assumption that the agents follow an individual objective is a very likely in real environments.

Under these assumptions, the outcomes in a distributed system are highly sensitive to costs of information and communication. The magnitude of the improvement in allocating efficiency depends critically on the cost of provide information to traders.

Query distribution: Depending on what content agents want, the performance in the distribution can suffer sensible variations. Random and Zipf query and content distribution are studied in our work. See [26], [74]. It is well–known that the query distributions of several popular applications, including DNS and the web, follow a power law distribution.[102]

5.3 Agent–Based Simulator

Pressure to make models more realistic can become as hard to interpret as the natural phenomena they try to explain. Agents representing individual behaviour within an agent–based market simulation show promising results in studying markets as evolving systems. An exchange economy is a system where the agents exchange the items that each one has in order to get a better distribution. In this context, the question is if the end distribution is efficient or not. See [165], [105], [166].

The implementation of a distributed market–based market has been applied in previous works such as [82], [113], [126], [180], [185]. Using simulation and real–world data show the performance of the models proposed. Simulation and real-world data show the performance of the models proposed. In our case, the simulator used for evaluating our work should be able to evaluate the three issues that shape the thesis: i.e. *Bartering Networks*, *Trading Paperclips* and *Distributed Barter-Based Directory Services.* Starting from a similar skeleton, three simulators have been customised in order to simulate the architecture that shares the following characteristics:

- The topology is generated by Pajek[2]. A program for analysis and visualisation of large networks.[21]

- The event–driven simulator is implemented in Java. The simulator was deployed following the same approach than the model. The first task was deployed a common library that will be used by the concrete simulators. The second task was to extend the simulator to each scenario.

- Results processing follows a similar pattern.

Agents representing individual behaviour within an agent-based market simulation show promising results in studying markets as evolving systems. In this computational framework for the study of complex system behaviours by means of controlled and replicable experiments are involved the following components:

- Graphical user interface (GUI) permits experimentation by users with no background in programming.

- Modular/extensible software support permits computational laboratory capabilities to be changed or extended by users who have programming skills.

The first advantage of agent based modelling is their capability to show how collective phenomena came about and how the interaction of the autonomous and heterogeneous agents leads to the genesis of these phenomena. Furthermore, agent–based modelling aims at the isolation of critical behaviour in order to identify agents that more than others drive the collective result of the system. It also endeavours to single out points of time where the system exhibits qualitative rather than sheer quantitative change [182]. In this light it becomes clear why agent–based modelling conforms with the principles of evolutionary economics. See [114], [115].

The second advantage of agent–based modelling, which is complementary to the first one, is a more normative one. Agent-based models are not only used to get a deeper understanding of the inherent forces that drive a system and influence the characteristics of a system. Agent–based modelers use their models as computational laboratories to explore various institutional arrangements, various potential paths of development so as to assist and guide e.g. firms, policy makers etc. in their particular decision context.

Agent–based modelling thus uses methods and insights from diverse disciplines such as evolutionary economics, cognitive science and computer science

[2]Pajek in http://pajek.imfm.si

in its attempt to model the bottom-up emergence of phenomena and the top down influence of the collective phenomena on individual behaviour.

In our human society, resource re–allocations are in most cases performed through markets. This occurs on many different levels and in many different scales, from our daily grocery shopping to large trades between big companies and or nations. The market approach to re–source allocation in the human society has inspired the Multi–Agent Systems community to construct similar concepts for MAS, where the trade is performed between computational agents on computational markets it is know as market oriented programming. See [191], [192], [84], [85], [47].

5.4 Conclusions

Given this background, the *resource allocation problem* (see [78], [171]) in a network with multiple, non co–operating agents can be recast as the problem of reconciling competition between self–interested, information–bounded agents. An effective mechanism for achieving this goal in the real world is the market economy. Examples of market–based methods: auctions, commodity markets, bartering. Concretely, this work is focused on barter trade pattern[3]. Thus resource allocation takes place against the assumption of *competition*, rather than *cooperation* between the components.

The most important objective of items distribution/reallocation application is that its users have everything that they need/want from the market. The important issue was in this case to know how a market–based approach that follow a bartering mechanism is successful with respect to the optimum assignment and the performance of the market.

A large number of goal–oriented entities interacting through social networks, each engaged in self–interested behaviour in a competitive way. The network connects each for the participants with others, but no one is connected to all others. The participants receive periodic communication from those with whom they are connected. Each individual is able of reasoning and take decisions on the information it receives (i.e. local knowledge) and they make a decision based on the benefit that comes from the exchange. The interactions between participants changes its environment. Therefore, decentralised market economies are complex adaptive systems, consisting of large numbers of agents involved in parallel interactions.[18]

Our overview of the problem is composed by distributed, open a large–scale environment with selfish agents trading in sparse networks, looking for its optimal beneficial.

[3]Barter is a self–enforcing response to absence of trust and functioning capital markets.

5.5 Summary

To conclude, this chapter explains the approach chosen in the thesis. How starting from a similar view point (i.e. the general framework), and assuming a set of guidelines, the three major ideas such as Bartering Networks, Trading Paperclips, Distributed Barter–Based Directory Services are developed.

Chapter 6

Bartering Networks

This chapter describes the model and experiments made in distributed bartering networks. The classical meaning of trading without money involves the establishment of a pairwise matching (i.e. formation of directed cycles of length two) which leads to a mutually beneficial exchange – i.e. quid pro quo. However, it is also possible to form arbitrary length directed cycles amongst agents. This forms a multilateral trade. Multilateral trade means that the quid and the quo are separated both spatially and temporally.

In a bartering economy, each agent relationship can be viewed as an instance of an Iterated Prisoner's Dilemma (IP). In each round, agents play part of a Prisoner. Let R_{local} denote the value of local resources and R_{remote} the value of remote resources. The reward R for cooperation for both traders is thus $R_{remote} - R_{local}$. The punishment M for mutual defection is zero. Finally, the temptation to detect T and the sucker's payoff S are R_{remote} and $- R_{local}$, respectively. Hence, we have the necessary conditions for a Prisoner's Dilemma: T>R>M>S.

To encourage large–scale cooperation amongst agents, strategies must be aware of defections and respond in an appropriate manner to encourage cooperative behaviour. Strategies based on reciprocity and feedback have these properties.[158]

Since users are considered to be *self–interested* rather than malicious, the best way to discourage defections is to offer an alternative that gives them better performance at a lower cost. It is useful for the system as a whole, and respects their desire.

An allocation procedure to determine a suitable allocation of resources may be either centralized or distributed. Clearly, the centralized approach is applicable to problems in which global information is available and agents are cooperative. Problems in which some agents want to keep their information private for competitive or other reasons, call for distributed methods ranging from coordination amongst cooperative agents (Durfee et al. [59]) to negotiation amongst competitive agents (Sandholm [159]).

The protocols needed for cooperative agents and those needed for self–interested agents differ. *Cooperative agents* can be assumed to take care of each others' tasks without compensation whenever that is beneficial for the society of agents. *Self–interested agents* need some compensation to take care of some other agent's task. This compensation can be organized as barter trade: one agent takes care of some of another agent's tasks if the latter agent takes care of some of the former agent's tasks. Barter trades that benefit both agents do not always exist even if it is profitable to move a task from one agent to another. Secondly, identifying beneficial barter exchanges is more complex than identifying one way transfers of tasks – especially in a distributed setting.

Agents may not know the whole state of the system such as preferences and ownership of the rest of the population. When the preferences are not common knowledge, self–interested agents often fail to explore win–win possibilities using existing protocols and end up with inefficient agreements. In the second approach a mechanism to overcome the informational restrictions is to add a list of preferences and ownership for each agent in the environment. Even the result of the allocation we could assume non–malicious agents when they are providing their preferences. Indeed, non–rational trades should be accepted even when the agents have all information to reach the goal optimal allocation.

In principle, a preference for longer paths should improve overall performance, as more agents are served, more agents are happy. On the other hand, agents prefer shorter paths as the search cost is lower, and the expected exchange volume is also higher, as the probability of a agent either disconnecting or completing is higher for longer paths. Assuming agents care less about global performance and more about their own benefit, there is no clear incentive to put additional effort into looking for longer paths.

A cycle indicates a possible trading arrangement. When a loop of proposed performative is accepted for all of its members the trades can be confirmed. The more participants that there are in an exchange, the greater number of people benefit from the exchange. The expectation is also that the benefit for all of the agents will also be improved over a transaction which involves only a small number of agents. See [83], [135].

An intrinsic problem that arises in such subsystems is that some of the users who should participate in a proposed path of exchanges may fail because users may learn of a better choice to exchange their own items, e.g., a direct exchange with one of the users not participating in proposed path.

The market get an optimal state when everyone has everything that they want. The maximal two–way exchanges are found through different versions of the algorithm of J. Edmonds, as discussed in Roth et al. [154]. Maximal two-way, three-way and maximal unrestricted exchanges are found through various formulations of the exchange problem as an integer programming problem. The integer programming formulation maximizes the number of exchanges subject to the constraint that the cycle size not exceed the specified exchange size (two–way, three–way, or unrestricted). In the case of three–way exchanges, we additionally constrain the solution to have the minimum number of three–way exchanges (and hence the maximum number of two–way exchanges) consistent with maximizing the number of exchanges. Extending to maximal unrestricted exchanges or multi–way bartering is a NP–hard problem.[136]

The questions to respond are:

- Where does non bilateral (i.e. pairwise) – multilateral trade lead?
- Where does bilateral – multilateral trade lead?
- When is a bilateral optimal allocation (i.e. an allocation can not be improved upon by bilateral trade) also Pareto optimal?
- When is a multilateral optimal allocation also Pareto optimal?
- When is possible to reach the global optimal?
- What is the difference between Pareto optimal, multilateral optimal, bilateral optimal, sub-optimal?
- How many trades are necessary and or sufficient to reach a X–optimal?
- What are the characteristics of an optimal sequence of interchanges given a particular starting point. Is it like search – what do local minima looks like?

Bartering networks in our work are equivalent to an assignment problem. It consists of finding a maximum weight matching in a weighted bipartite graph. The assignment problem could be resolved with the Hungarian algorithm. This is a combinatorial optimization algorithm which solves assignment problems in polynomial time ($O(n^3)$).

Touching algorithms are:

- Assignment allocation problem or weighted bipartite matching.
- Weighted vertex disjoint cycles.

6.1 The Bartering Network Model

The model of the *bartering network* problem has the following characteristics:

- The studied market is composed of participants that offer items.
- Participants are located in a network and are linked to a small quantity of other participants.
- The links amongst participants are static, but the participants that form the network have periods of being switched on and off (to simulate variable up-times of participants).
- Each item has a unique level of satisfaction associated with it for each agent in the system (utility or level of satisfaction – *los*).
- Initially the items are randomly assigned to participants.
- Trades are conducted by means of bartering.
- Trades modify the global *los*.
- Members take only local decisions.
- Information about available items is only available from local connections.
- Members can only trade with directly connected neighbours.
- Members only decide to trade when the trade is immediately beneficial.
- Global performance is measured as the sum of *los* over all participants.
- A steady state is achieved when no more trades are possible.

6.2 Implementation Overview

The first approach to improve the performance of bilateral exchanges is to expand the number of participants in the bilateral exchange protocol.

- **2–way exchange:** 2–way exchanges is showed in Figures 6.1 and 6.2 and the Algorithm 2 – 2–way protocol. The algorithm shows that an exchange will only be done if it is beneficial for both buyers and seller.

Algorithm 2 2–way protocol

p_B sends req(o_2)
p_A saves B wants o_2
if (p_A has o_2) & ($PV_{p_A}(o_1) > PV_{p_A}(o_2)$) **then**
  p_A sends ack(o_1:p_A,o_2:p_B)
end if
if (p_B has o_1) & ($PV_{p_B}(o_1) < PV_{p_B}(o_2)$) **then**
  p_B sends ring(p_A:o_2,p_B:o_1)
end if

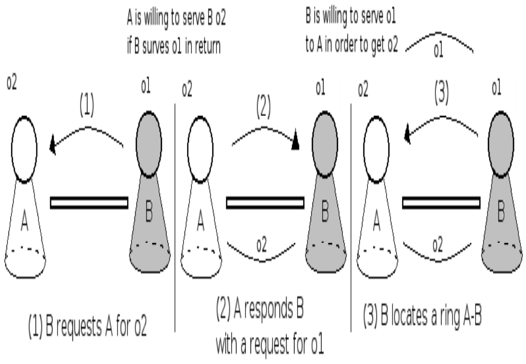


Figure 6.1: 2–way exchange.

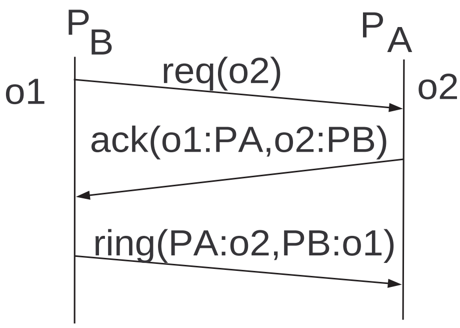


Figure 6.2: 2–way protocol.

Algorithm 3 3–way protocol

p_B sends req(o_2)
p_A saves B wants o_2
p_A sends req(o_1)
p_B saves A wants o_1
for $i = 0$ to IRQ_{p_B} **do**
  p_B sends ack(o_2:p_B,o_1:p_A,o_3:p_{O_i})
  p_{O_i} saves A wants o_1
  p_{O_i} saves B wants o_2
  p_{O_i} saves B has o_3
  if (p_{O_i} has o_1) & ($PV_{p_{O_i}}(o_3) > PV_{p_{O_i}}(o_1)$) **then**
    p_{O_i} sends ring(p_A:o_2,p_B:o_3,p_{O_i}:o_1)
  end if
end for
if IRQ_{p_B} has not received the ring **then**
  for $i = 0$ to Neighbour $p_B \notin IRQ_{p_B}$ **do**
    p_B sends ack(o_2:p_B,o_1:p_A,o_3:p_{N_i})
    p_{N_i} saves A wants o_1
    p_{N_i} saves B wants o_2
    p_{N_i} saves B has o_3
    if (p_{N_i} has o_1) & ($PV_{p_{N_i}}(o_3) > PV_{p_{N_i}}(o_1)$) **then**
      p_{N_i} sends the ring(p_A:o_2,p_B:o_3,p_{N_i}:o_1)
    end if
  end for
end if

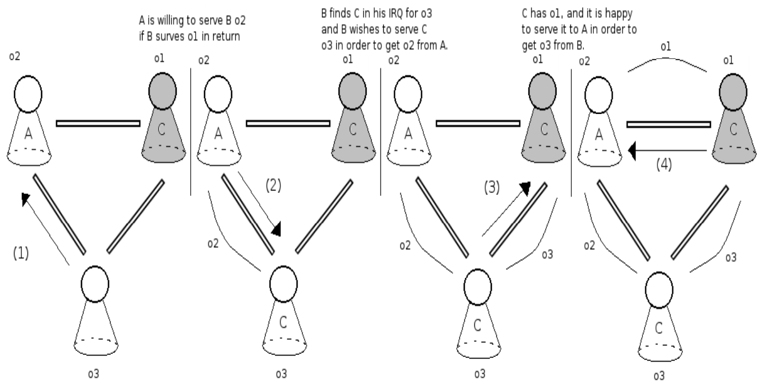


Figure 6.3: 3–way exchange.

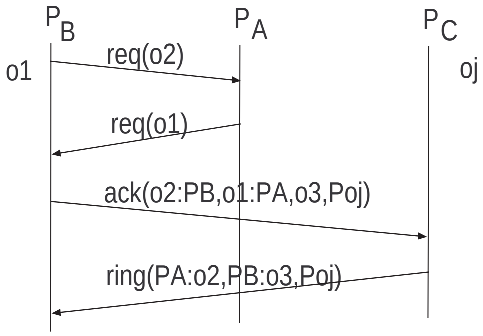


Figure 6.4: 3–way protocol.

- **3–way exchange:** 3–way exchange is show in Figures 6.3 and 6.4 and the Algorithm 3 – 3–way protocol. In this case, three participants are involved in the exchange.

- **3–way recursive exchange:** Figure 6.5 shows examples of 3–way recursive exchanges.

  In Figure 6.5 the first 3–way exchange $E\ o_3 \Leftrightarrow o_4\ B$ and $A\ o_4 \Leftrightarrow o_2\ B$. The second 3–way exchange E $o_3 \Leftrightarrow o_4\ B$ and $A\ o_4 \Leftrightarrow o_2\ B$.

  Between the first and second 3–way exchange the agent B is taking a risk because during these two exchanges another agent can exchange with an agent from the second 3–way exchange such as E and A.

- **Limited markets:** A market mechanism provides a powerful way to regulate exchange between members of a community, in which each one of these members wish to maximize its utility/satisfaction. This section shows pitfalls in market exchanges.

  - **Time limited markets:** In this case, the number of interactions in a given market place is limited (i.e. time limited). Concretely, this means that in a time the system will cease functioning. For example, if all files are exchanged, a certain deadline passes or after some signal is given. In a time unlimited market, members cooperate with the objective of getting a benefit in a long term future[1]. However, when the time is limited, the hope of a future benefit is not apparent because members know that in a concrete time the game will finish. To understand the effect of this fact,

[1] The shadow of the future [15].

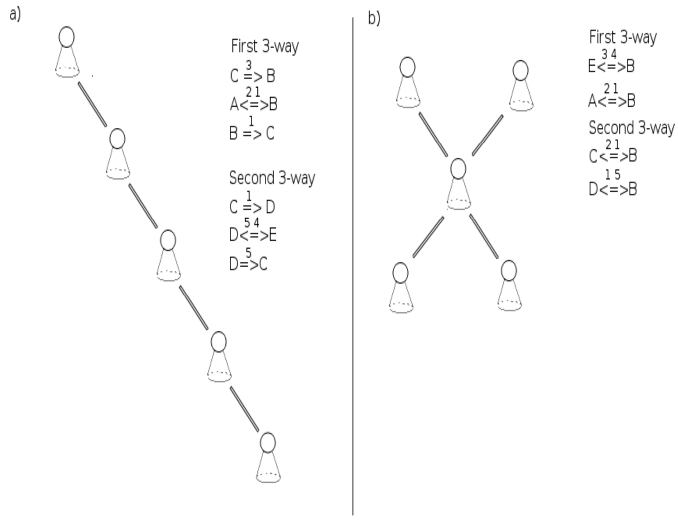


Figure 6.5: Examples of 3–way recursive exchanges.

we suppose that players know that a game has exactly n rounds. Then, no matter which round has been reached (say $n-1$) the agent is aware that the incomes kept will no longer be useful after the end of the game. Hence no agent will offer content in the last round (round n). Subsequently this also means that the incomes kept is not useful not only after the end of the game but also not in the last round. Similarly no agent will offer content in round $n-1$ and so forth. By repeating this argument many times, rational agents would deduce that they should not offer content at all (unless their motivation changes because someone else offers something they want). In a simulation where an agent can chose between two strategies, the only difference between the two strategies (s_1,s_2) and (s'_1,s_2) is that in the period t the first strategy chooses C (cooperate – offer content) and the second strategy chooses D (defect – not offer content). Until the end T of all iterations the benefits of choosing the strategy (s'_1,s_2) will be greater than (s_1,s_2). This concept is clearly analogous in the well known game theory known as the Prisoner's Dilemma (PD) [15] result for games of known duration.[2] The conflict between the individual and collective interests is expressed in this game, which has implications in real life in areas like policy, society, economy. Concretely the relation is with a subset of PD, named PD with

[2]PD rules are explained in detail in [141].

finite repetitions.

- **Content limited markets:** This hypothesis considers that the content is limited even if time were unlimited. In such world the number of total different content items is finite and unchanging. In an ideal world all members in the market should obtain all contents that they want. If agents are aware of this fact, this goal will not be achieved. When an agent obtains all the content that it desires (i.e. satisfied agent) it is conscious of the fact that it has all it may want, so a rational agent would cease offering content. The reason is similar to that in the previous case: the agent will, in the future, not derive benefit. This fact entails that other non–satisfied agents may not obtain all the content they desire if some of it is hold by satisfied agents. Once it is known that there is no more new content to obtain, the exchanges opportunities tends to zero. In turn, this causes the agent to become resistant to offering content before all possible useful exchange have been made. Only altruists would continue once they had obtained everything they needed.

- **Time and content limited markets:** Under these restrictions, a market has little hope of functioning. An interesting example of this can be seen as exemplify by Clive Thompson in his article "Not With a Bang but a Whimper" about the game Asheron's Call 2[3], an online game scheduled to cease functioning in December 2005. Characters in the game could pick up items such as tools, armours and weapons at once within a container and they can trade these items with other players. When the game was flowering the characters used to sell their items but when the game shut down was first announced, the majority of players left the game. This happens because without a sense of future capitalism ends. In other words there is no demand in a condemned world.

These markets were studied to investigate their fruitfulness. However, they will not be investigated further as, in the next chapters, only non–limiting markets will be dealt with.

• **Information:** Information is a powerful tool for the agent buyer–seller in the decision–making process. Information is shaped by the detection of needs and network structure. With respect to the detection of needs, two different kinds of information are studied:

[3]http://ac2.turbine.com

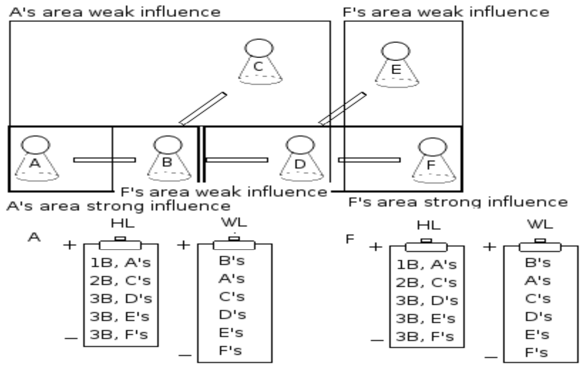


Figure 6.6: List of preferences and area of influences by agent A and F and the list of preferences and ownership for agent B and F.

- Lists of preferences (i.e. want–list WL): The items that the agent wants.
- Lists of ownership (i.e. have–list HL): The items that the agent has.

List of preferences: This list contains the items preferred by the individual, the items preferred by nearer neighbours, and finally the items preferred by far neighbours, in this order. The order in the list is important, because this determines the relevance of the items.

Figure 6.6 shows the intention that follows this list as distance–based propagation with the idea to take advantage of the spatial locality. By means of bold and non–bold boxes, the degree of influence a node has over its neighbours. A bold line indicates a greater degree of influence than a non–bold line. Concretely the figure shows the influence that agent A and F have with respect to their neighbours. For example, agent B is more influenced by A than F. This implies that in $B's$ list of preferences items wanted by agent A appear before items wanted by F. In the want–list the most valuable items appear as the top entries, and the least valuable items are at the bottom of the list.

List of ownership: This list contains the items that an agent has, the items that the nearer neighbours have, and finally the items far away neighbours have.

Without propagation, each agent has used knowledge of their neighbours in order to evaluate possible exchanges of items. However, while some trades can occur if items should travel multiple hops in sparse topologies, it could restrict market activity. In our study, a list of preferences has been added. This list contains the items that neighbours desire and the information that will be used to make trades. The ownership list contains items and links where can be obtained. The propagation of preferences/ownership takes the steps listed in Algorithm 4:

Algorithm 4 Propagation of preferences

> **for** $i = 0$ to all neighbours **do**
> $agent_i$ sends(preferences)
> $agent_i$ arranges(preferences)
> **end for**

Three extensions have been implemented and the results obtained from the experiments have been compared with the original propagation.

- **Extension 1:** Avoid the re–sending of preferences. In order to avoid a neighbour re–sending duplicate preferences to the original owner, this extension re–uses that otherwise wasted space.
- **Extension 2:** Promoting the propagation of preferences in agents with few links and to promote the propagation of neighbours in agents with many links. The idea behind this extension is to make that agents with few links put more wishes in the list of preferences. It gives more emphasis to the desires of the agent. With respect to agents with many links, the extension gives more emphasis to the preferences of their neighbours.
- **Extension 3:** In terms of extending the propagation of preferences, the list of ownership provides information which allows agents to direct their demand propagation mechanisms in the network.

This additional information has a number of consequences. The first one is that the quantity of trades increases because agents are not only trading taking into account their preferred items. Instead of this, they extend their range of preferences, treating the preferences of their neighbours as their own preferences. This increases the probability that double coincidence of wants will be achieved. However this increases the traffic in the network.

6.3 Experiments

6.3.1 Experimental Configuration

Bringing together descriptions of the problems from the previous section, the properties of the model are the following:

- Initially, items are randomly assigned to agents.
- All the agents follow a $GDAs$ behaviour.
- $GDAs$ is linked with a set of agents, depending on the network topology.
- The simulator offers the opportunity to make an action per cycle.

6.3.2 Topology Variation

The goal of the experiments is to investigate the importance of the variations in the topology with respect to the quantity of links. Looking for this goal we vary the topology of the network with respect to degree. Table 6.1 gives an overview of the measures related to the scenarios studied. This range of scenarios allows us to recognize when the market is affected by the lack of links. The scenarios share the same set up. The only altered parameter has been the quantity of links. In these scenarios the quantity of links decreases from scenario 1 to scenario 6. From scenario 1, that has a fully connected structured with 124,759, to the scenario 6 that only has 779 links. For each scenario, a set of different network topologies have been tested in order to verify that the results are not dependent on a concrete wired network. Figures 6.7 and 6.8.

In order to determine the quantity of links required by the market (W), it is necessary to know the diameter, average path length and the average degree in the network. Also, in all of the scenarios, the number of unreachable pairs is equal to zero to ensure a graph is not disconnected. The *diameter* (D) of a network is defined as the maximum distance amongst all distances between any pair of nodes in the network (i.e. the longest shortest path between any pairs of nodes). The *average path length* (L) of a network is defined as the mean distance between two nodes, averaged over all pairs of nodes (i.e. average distance amongst reachable pairs of nodes). Finally, (R) is the *average degree* of the network.

In order to contrast the effect that the quantity of links has on the performance of the market, a set of scenarios where the quantity of links has

Scenario	Quantity of links	Average path length	Diameter	Average degree
s1	124,759	1	1	500
s2	5,457	2.72	4	16,07
s3	3,897	2.90	4	11,47
s4	2,338	3.02	5	6,88
s5	1,559	3.57	6	4,59
s6	779	5.34	11	2,29

Table 6.1: Network measures

been varied, has been simulated: from a fully connected topology to a quasi non–connected topology.[177]

Figure 6.9 shows the progression of the *los* in a simple bartering environment.

Up until now, each node has used knowledge of their neighbours to evaluate possible exchanges of objects with its neighbours. However, while some trade can occur in which objects travel multiple hops, it is clear that sparse topologies significantly restrict market activity. In order to explore what happens when more information is available, applying propagation of preferences, every node is now assigned a propagation list. This list contains the items that neighbours desire and the information will be used to make trades. Results of these simulations are shown in Figure 6.10.

It can be seen from the simulations that using propagation of preferences, the whole *los* in the market increases.

Results of these simulations are shown in Figure 6.9. In the initial time (i.e. from time 0 to 15) behaviour is similar to that of the previous case. In scenarios 1, 2 and 3, the *los* is above 9,000 points. In scenario 4 the *los* is near to 8,500 points. When the network has 1,559 links (i.e. scenario 5) the *los* is around 7,500 points and in the scenario 6 is where the value obtained is farthest from the optimal *los*. In this case, the worst results appear when L is greater than 3. This shows that propagation begins to extend the range of trade, yet only in a limited way.

It can be seen from the simulations that using propagation of preferences, the whole *los* in the market increases. The results show that in scenarios with a small number of links the *los* is substantially reduced.

Figure 6.10 shows the *los* when the market is using propagation of preferences based on extension 1 and extension 2. The experiments shown here, focus on scenarios 4, 5 and 6 as these are the scenarios where there are significant variations in the *los*. The first column of the set is with the market

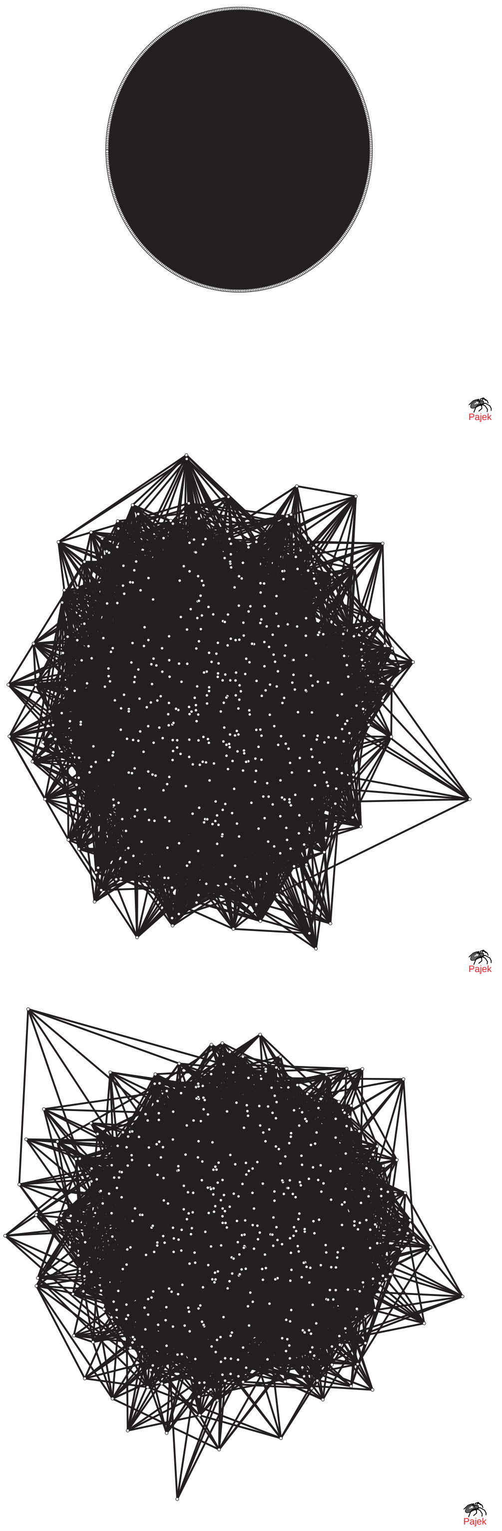


Figure 6.7: Structure of the trade network from scenario 1 (i.e. fully connected) to scenario 3

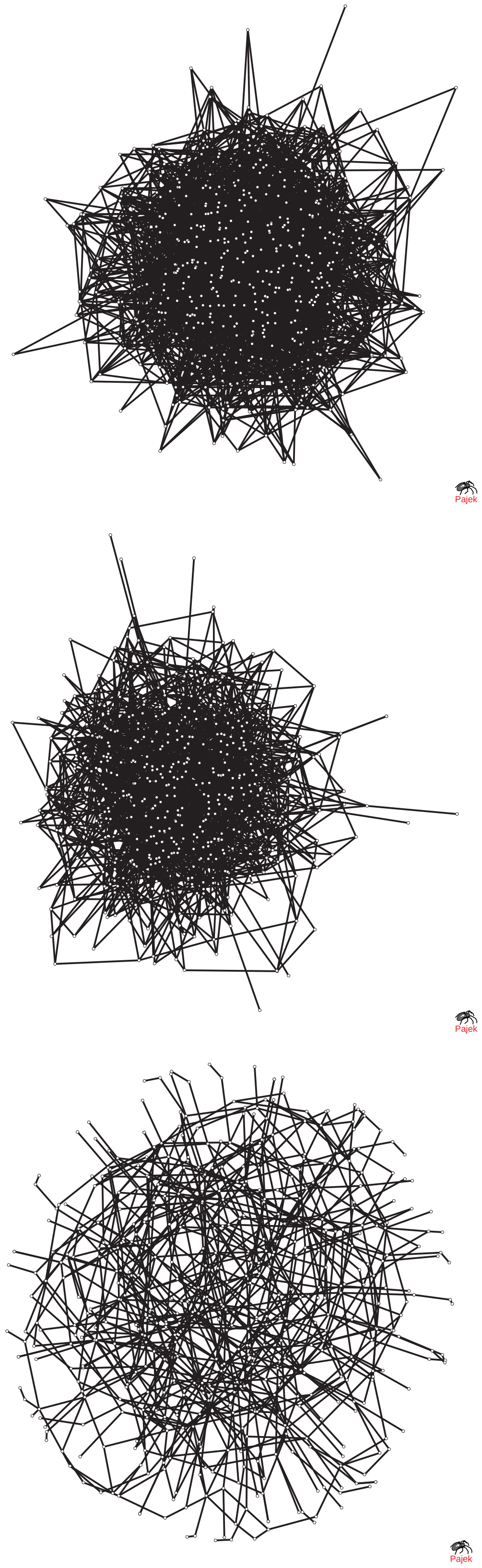


Figure 6.8: Structure of the trade network from scenario 4 to scenario 6 (i.e. quasi non–connected).

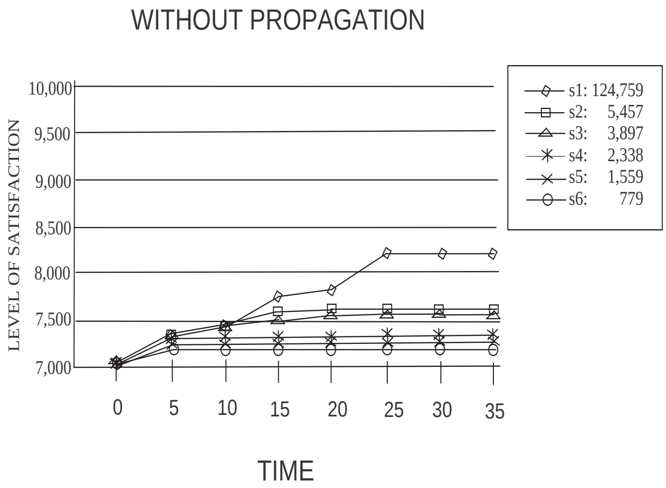


Figure 6.9: Results working without propagation. In the graphs, x–axis represents the past of time and y–axis the *los*.

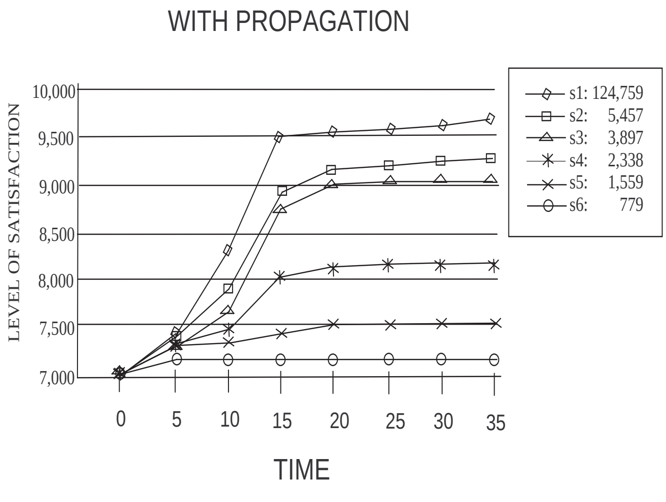


Figure 6.10: Results working with propagation. In the graphs, the x–axis represents the passing of time and y–axis the *los*.

using the original propagation, the second column is the *los* obtained with extension 1 and finally the last column is related to the extension 2. The results reveal that with 779 links neither extension 1 nor extension 2 work properly. The low quantity of links makes this market a sterile market, as much for the original approach as well as for the proposed extensions. In scenario 5 with 1,559 links, the results using extension 2 are better than in the original and extension 1 approaches. In scenario 4, both extensions improve the results of the original approach.

6.4 Conclusions and Future Work

The most important objective of goods distribution application is that its users have everything that they need/want from the market. The important issue in this case is to know how a market–based approach is successful with respect to the optimum assignment, and which elements affect the performance of the market.

The results show that the quantity of links has an impact on the performance of the market. In fully connected networks, all agents are free to trade with any agent in the market. Optimal allocations are possible amongst agents with few trades. The drop in one–to–one trades is less than, for instance, where a chain of one–to–one is necessary for trades as occurs in many spare networks. Furthermore the market performance is affected by the use of propagation of preferences. Even simple propagation can significantly change the efficiency of the market. Focusing our efforts on content distribution:

- There exist centralized algorithms, but can we get close to a distributed way without altruists needing to be present?

- Given N agents each with randomly assigned goods, how do you design mechanisms by means of which they can improve their overall satisfaction without the need for altruistic distributors.

The General Framework chapter described the bartering environment. This chapter together with the following of chaptes follow the assumptions and game rules outlined in the General Framework chapter.

- The Bartering Networks chapter studies the relevance of information (i.e. propagation and quantity of links) and the 2–way versus 3–way exchange protocol.

- The Trading Paperclips chapter reviews the competition between participants in the market, therefore this chapter is related to the performance of the market.
- The Distributed Barter–Based Directory Services chapter shows the importance of topology in a directory services and the propagation of the preferences i.e. information distribution.

Key issues for future work include:

- To apply different market rules in order get closer to the optimal assignment as well as in the quantity of trades necessary to get to this assignment, considering that exchange is costly.
- The comparison between assignment problem and content distribution to other market scenarios, for example to have a set of files for an agent could be considered more valuable that to have only some parts (e.g. chapters of some series), with copies.
- In terms of extending the propagation of preferences, work now focuses on propagation which has longer and more directed reach across multiple nodes in a network. An important first step that is the propagation of ownership, who owns which objects. This provides a counterpart to demand information which allows agents to direct their demand propagation mechanisms in the network.

6.5 Summary

To conclude, this chapter shows:

- **Markets properties and limitations:** Limiting time and/or content not everyone can obtain all that they want.
- **Topology:** The topology has a direct effect on the performance of the market.
- **Information:** That the quality and quantity of information from one individual to another, in our case propagation of preferences, has a positive influence on the performance of the market.
- **Long path:** Increasing the number of participants in exchanges is increasing the opportunities and complexity in the protocol.

Chapter 7

Trading Paperclips

This chapter starts with the story of Mr Kyle MacDonald who, by mean of a sequence of swap bartering exchanges between July 2005 and July 2006 managed to trade from turns a red paper–clip into a house in the Town of Kipling Saskatchewan [119].[1] While much of the press coverage of the amazing story focuses on the role of the internet in mediating and discovering trades, the events are also interesting from a trading point of view. The story is composed of a *goal driven agent* starting with paper–clip and wanting a house, as well as a set of *passive agents* who have different items and are in the market expecting profitable exchanges. This story reveals that no matter what item you have, what matters is reaching the right people to trade with. What is more important than ownership is to find a beneficial chain of trades in the market. This starting point raises many issues such as: "How does the goal driven agent know that an exchange gets them closer to their dreams?", "How many goal driven agents can make their dreams reality?" and more generally "What conditions are necessary in the market to assure that the goal driven agent will get the desired item?".

Although the motivation for making trades amongst the participants in Kyle's story[2] is unknown, some of them may have been motivated by *altruism.* In this case, altruism can be defined as a willingness to accept something of lower value in order to help Kyle on his way or to obtain other peripheral secondary in–direct benefits (such as a desire to participate in an interesting experiment). However, it is likely that the majority of participants were probably making trades in which they at least sought significant value (if not full value) – Kyle was deliberately seeking out potential exchange partners who valued his current item the most. Further, while the motivations

[1] http://oneredpaperclip.blogspot.com

[2] One Red Paperclip: Or How an Ordinary Man Achieved His Dream with the Help of a Simple Office Supply.

of the original participants are unknown, a key question in such scenarios is – “Would such a general mechanism work if there were no altruists at all?”. Scenarios where self–interested agents barter/exchange resources in order to increase their individual welfare are ubiquitous ([111], [162]) examples include The trueque club, Peerflix (DVDs)[3], Read It Swap It (books)[4], Intervac (holiday houses)[5] as well as Kyle MacDonald’s story. In all of these examples the motivation is to exchange what you have, and get what you need without cash and to obtain a satisfaction or benefit. And hence it is of interest to understand whether such trading patterns could arise.

The One Red Paperclip is a classic example of arbitrage [55] – where value is extracted by playing on the asymmetries valuations. Betting exchanges have many similarities to the Kyle’s experiment. Betfair[6], Betdaq[7] and other similar betting exchanges have huge turn over now and many billions of pounds are matched each month on these markets. In betting exchanges an arbitrageur exploits existing price discrepancies when bookmakers’ prices differ enough that they allow to back all outcomes and still make a profit. In paperclip exchanges Kyle exploits personal value discrepancies, taking advantage from the personal valuation differential between agents. Other similarity is that sports arbitrage are more accessible to everyday people because of the internet as in the Kyle’s experiment a large–scale market benefit. But there are still barriers which stop everyone from being successful in both scenarios. Both scenarios take capital, time, organization and energy to make profits.

Furthermore, bartering has been used in commercial applications such as: SwapAce[8] and Worldwide Barter Board[9] or SwapTree[10]. These systems are innovative online marketplaces where individuals or communities trade and interact with each other - which may potentially exhibit similar dynamics to those studies in this paper. In particular participants are not motivated by pure market value – but by value to them at a particular point in time.

Kyle’s and other similar experiences show alternative economic visions to normal electronic transaction which are anonymous and money oriented, by relying on personal encounters which are mediated by useful trades for both parts of the negotiation. This is a more basic trading approach but opens

[3]Peerflix in http://www.peerflix.com
[4]Read It Swap It in http://www.readitswapit.co.uk
[5]Intervac in http://intervac-online.com
[6]Betfair in http://www.betfair.com
[7]Betdaq in http://www.betdaq.com
[8]SwapAce in http://www.swapace.com
[9]Worldwide Barter Board in http://www.worldwidebarterboard.com
[10]SwapTree in http://www.swaptree.com

new opportunities for exchanging and negotiation studies in large–scale social context. The One Red Paperclip is a search problem that has the following components:

- **Initial state:** Includes the board position and identifies the player to move.
- **Successor function:** Returns list of (move, state) pairs, each indicating a legal move and the resulting state.
- **Terminal test:** Determines when the game is over (i.e., when we are in a terminal state).
- **Utility function:** Gives a numeric value in terminal states (i.e., -1, 0, +1 in chess).

There are four criteria in designing a search algorithm:

- **Completeness:** The algorithm guaranteed to find a solution if a solution exists?
- **Time complexity:** This is often measured by the number of participants visited by the algorithm before it reaches a goal node.
- **Space complexity:** This is often measured by the maximum size of memory that the algorithm once used during the search.
- **Optimality:** The algorithm guaranteed to find an optimal solution if there are many solutions? A solution is optimal in the sense of minimum cost.

Path finding addresses the problem of finding a good path from the starting point to the goal. This problem has the following features:

- **Large–scale or non–large–scale:** Peer-to-Peer, MAS and Grid technologies enable an arbitrary large number of users to participate in distributed services like content distribution or collaboration tools.
- **Two player or teams of players:** In environments with multiple self-interested agents, an agent's outcome is generally affected by actions of the other agents. Consequently, the optimal action of one agent can depend on the actions of others.

- **Imperfect or perfect–information games [72]:** From Game Theory, the concept of imperfect information is observed if a player does not know exactly what actions other players took up to that point. Technically, there exists at least one information set with more than one node. If every information set contains exactly one node, the game is one of perfect information.

- **Zero–sum or non–zero sum games:** In game theory and economic theory, zero-sum describes a situation in which a participant's gain or loss is exactly balanced by the losses or gains of the other participant(s).

- **Competitive or cooperative games:** In competitive environments [6] agents have distinct goals but may still interact to advance their own goals whereas in cooperative environments [116] agents work toward achieving some common goals.[11]

- **Deterministic or non–deterministic algorithm:** The transition from one state to the next is not necessarily deterministic; some algorithms, known as probabilistic algorithms, incorporate randomness.

- **Complete and optimal search:** A search method is called complete when it is guaranteed to find a solution if there is one. A search method is said to produce optimal solutions when the method is guaranteed to output the highest–quality solution when there are several different solutions.

- **Irreversible or non–irreversible changes:** An example of irreversible change is the chemical synthesis:
  - The operations can be: Add chemical x to the pot, change the temperature to t degrees.
  - These operations may cause irreversible changes to the potion being brewed.
  - The order in which they are performed can be very important in determining the final output.
  - Non partially commutative production systems are less likely to produce the same node many times in search process.
  - When dealing with ones that describe irreversible processes, it is partially important to make correct decisions the first time, although if the universe is predictable, planning can be used to make that less important.

[11] http://www.thegamesjournal.com/articles/FamilyPastimes.shtml

The work in this chapter develops a simple agent population model based on active/goal–driven and passive agents with ranges of personal value distributions for the items they own. Then is applied a simple trading mechanism to show that scenarios such as Kyle's story are indeed possible for goal driven agents without relying on altruistic behaviour. The work characterizes the conditions necessary for this to occur and goes on to study the emerging dynamics as an increasing number of goal striven agents become active. The main contributions are:

- Providing an intuitive model for such open bartering environment.
- Showing that the effect can be seen in simple populations of agents.
- Showing that the market does not require altruistic agents to be present.
- Studying the dynamics of what happens if there are many agents pursue goal–driven strategies:
  - Showing that as the balance changes between goal driven agents (GDA's) and passive agents (PA's), goal driven agents can no longer achieve their goals.
  - Analysing failure states.

7.1 The Trading Paperclips Model

The model developed for the scenario is relatively simplistic, but captures the main elements of Kyle's trading environment. The model consists of the following components (see Figure 7.1):

- A population of agents in which each agent plays one of these two roles:
  - ***Goal driven agents*** (*GDA*)**:** These agents try to reach a dream (i.e. an item with a value that seems infinite to them and is also very high on the general market value ranking). The initial item of property this type of agent owns is considered low in the general market ranking. The agent deliberately seeks rich/beneficial trading encounters in order to move upwards in market value.
  - ***Passive agents*** (*PA*)**:** These agents have an item and do not seek any particular new item, however they know a good deal when they see one. In the case that a GDA tries to trade with a PA, the PA only accepts it if it is beneficial – i.e. its own satisfaction is increased by the trade.

- **A list of items:** An item is any type of private good such as food, clothing, toys, furniture, cars etc. This list follows a strict order in function of a general *market value* (MV). MV is the value fixed and determined by buyers and sellers in an open market.

- **Personal value:** Each agent has a *personal value* (PV) for each item in the market (and hence for each item they own). This PV differs for each agent in the market with a statistical deviation (which may be positive or negative) – in other words an agent may value certain items at above or below general MV. $MV_i(g_j)$ and $PV_i(g_j)$ represent the MV and PV respectively of the agent$_i$ with respect to the item g_j.

- **Links:** Each agent is connected to the rest of the members in the market.

- **A set of ranges:** A range contains multiple items with the same MV and a range of possible PV restricted to two values [-σ, +σ] related to this MV. Without this partition the cost of finding all possible ways would be too expensive[12].

- *The exchange strategy:* An exchange between two agents GDA and PA is accepted iff there exist two items g_i, g_j, where $_{j=i+1}$ that are in neighbouring ranges such as:

$$\{g_i \in GDA, g_j \in PA\ : PV_{PA}(g_i) > PV_{PA}(g_j)\ and\ MV_{GDA}(g_j) > MV_{GDA}(g_i)\}. \tag{7.1}$$

  Where in the equation 7.1:

  - $PV_{GDA}(g_j) > PV_{GDA}(g_i)$ could not be true because the GDA is more concerned about MV for future trades than in PV. Nevertheless, it is natural that $PV_{GDA}(g_j) > PV_{GDA}(g_i)$.
  - $PV_{PA}(g_i) > PV_{PA}(g_j)$ could not be true because the PA is more concerned about its PV than in MV.

    An example is when the GDA has the item A and $PV_{GDA}(B) =$ 60, $MV_{GDA}(A) = 65$ and $PV_{GDA}(B) = 70$ and agent PA has an item B and a $PV_{PA}(B) = 65$, $MV_{PA}(B) = 70$ and $PV_{PA}(A) =$ 75. Under these conditions GDA and PA can make the exchange of items A by B (see Figure 7.2).

Nevertheless, the equation 7.1 is not enough to assure that the item obtained in the exchange that GDA gets is one of the items that takes

[12] This is reviewed in section 7.2– Using backtracking

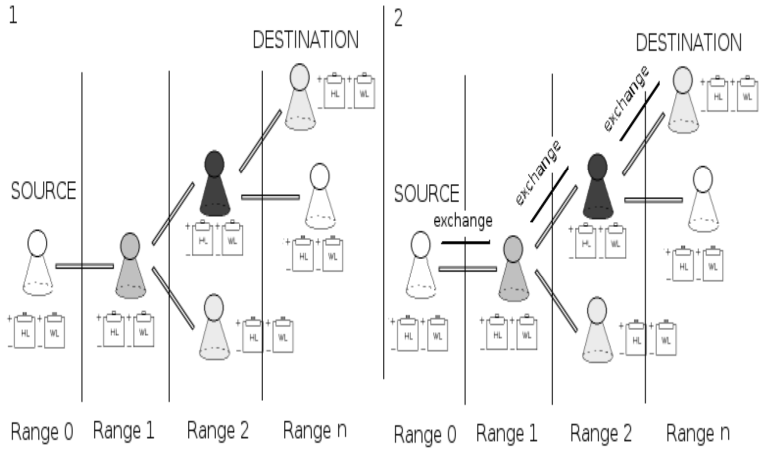


Figure 7.1: A goal driven agent wants to turn an item with low value into an item with high value by means of a sequence of exchanges.

part of the chain of items to obtain the desired item (i.e. the house). The equation only guarantees that the trade is profitable in both sides and therefore it could be done.

The work experiments with a number of cases based on the following general parameters and for the cases of a single GDA and of multiple $GDAs$.

- Initially, items are randomly assigned to agents. One item per agent.
- The number of ranges is fifty. Each range is composed of one hundred items. Range $_1$ contains the items of lowest value and in range$_{50}$ contains those of highest value.
- The market is composed of one hundred agents which have items.
- The GDA knows where all the rest of the agents are located and can communicate with them (i.e. the system is fully connected).
- Items have an unique MV but each agent has its own PV of the item.
- Trades are conducted by means of bartering. An exchange is always between a GDA with an item from range$_x$ and a PA with an item from range$_{x+1}$ (see Figure 7.2).
- The GDA only take local decisions.

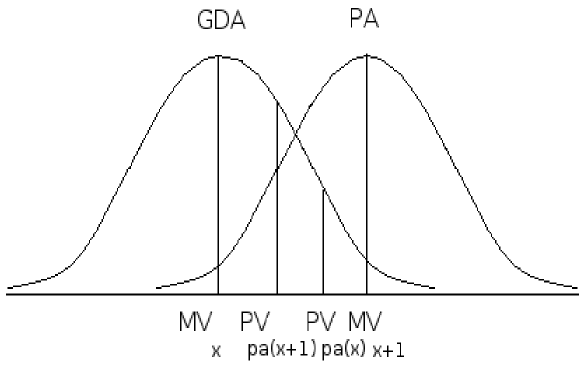


Figure 7.2: The GDA is increasing its MV and the PA is decreasing its MV but it is increasing its PV.

- $GDAs$ only trade when the interchange is immediately beneficial according to general MV. The PAs only trade when the interchange is immediately beneficial according to its PV.
- The PV of the items follows a $\sim \mathcal{N}(\mu, \sigma)$. Then, μ_i - μ_{i+1} represents the distance between ranges or between cluster of items with the same MV and σ represents the variation of PV.
- In each of our graphs, each data point is an average of ten simulations, and we provide statistical significance results to support our main conclusions.
- A blocking situation is when a GDA wants some item but one of the agents does not trade until it gets the GDA offers the items the agent itself desires.
- A *steady state* is achieved when the $GDAs$ reach the desired item.
- The model can be generalized to accommodated multiple GDA agents, all with the same behaviour.

The exact adjustment path and the speed of movement along that path can be crucial to a policy achieving its specified goals. Other issues:

- **Single and multiple goal driven agents (**GDA**):** The most basic form of the systems to be explored is that in which there is only a single GDA looking for a desired item which has the highest value in the market (i.e. from a paperclip to a house). Once proven that an isolated GDA can reach an item from the last range under some configurations, the next step is to balance the quantity of PAs (i.e. PAs are not looking for beneficial trades) and GDAs, to check the behaviour of the market with other distribution populations. Therefore, the strategy is to increase the percentage of GDAs in the market in order to reveal the dynamics that appears in front of the variation of populations.

- **Backtracking:** Kyle's experiment can be seen as a *path finding problem*[13] where problem are focused on finding an efficient, and possibly optimal path a some initial state to some final state. The aim for any GDA is to reach the desired item in the last range. In a single search process when it is not possible to progress, the process ends. This does not mean, however, that other paths will not be possible (i.e. other exchanges could carry on to satisfy the GDA). In order to look for other paths a classical backtracking algorithm has been applied [143]. Until now, the searching process works without backtracking (BT), this means once the search process arrives at a range where it is not possible to advance, the process ends (i.e. monotonically) as is showed in the monotonic search algorithm. However, the BT algorithm [108] tries to overcome this situation by looking for new paths (i.e. non–monotonic search). In the worst case, the classical BT algorithm has an exponential cost. In order to reduce this cost the search space has been restricted. To apply BT is necessary to include downward exchanges. Two types of exchanges are considered (see Figure 7.3):

  - **Upward exchanges:** An exchange between an GDA with an item from range$_x$ and PA with an item from range$_{x+1}$.
  - **Downward exchanges:** An exchange between an GDA with an item from range$_{x+1}$ and PA with an item from range$_x$. This type of exchange will be done when a GDA makes a backtrack.

- **Value–enhance action**: This action allows the $GDAs$ to improve the value of an item of certain categories. For example, a GDA can clean an old item adding an extra value to this item for the rest of members in the market. Figure 7.4 shows a GDA with item$_x$ and a PA with item$_y$ where $MV(item_y) > MV(item_x)$. In a) PA evaluates that $PV(item_x) < PV(item_y)$ for that reason PA prefers to not exchange with the GDA. However, in b) GDA value–enhances the item$_x$ and for

[13]Path finding problems are focused on finding the path from some initial state to some final state. When solving this type of problem, the start and end points of the search might be known in advance. Finding an efficient, and possibly optimal, path between the start and end state is the goal.

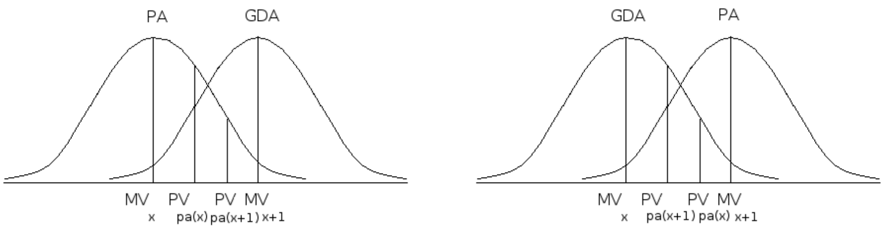


Figure 7.3: a) Upward exchange. The GDA is increasing its MV and the PA is decreasing its MV but it is increasing its PV and b) Downward exchange. The GDA is decreasing its MV and the PA is increasing its MV and PV.

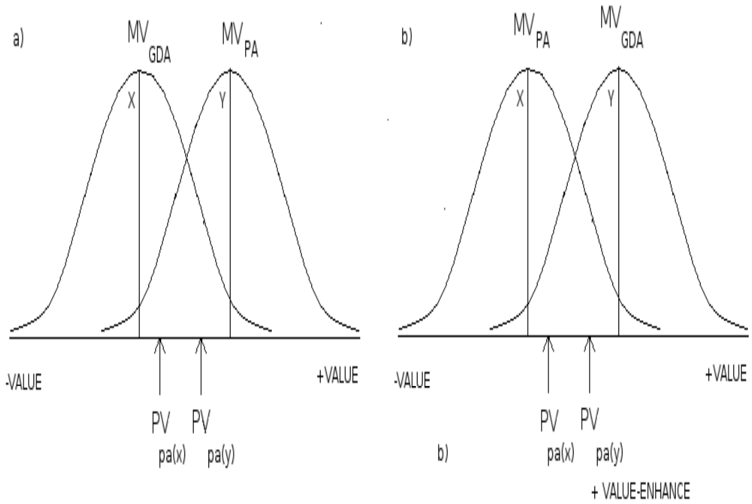


Figure 7.4: Non–value–enhancement versus value–enhancement situation.

the PA in this case will be $PV(item_x) > PV(item_y)$ making possible the exchange. Each GDA can follow one of the following strategies:

- To exchange (E): The GDA only trades up.
- To value–enhance first, to exchange after (VEE): In this case the GDA is able to value–enhance items belonging to a set of categories. Firstly, the agent value–enhances the item when it is possible. If the item cannot be value–enhanced it is because the item does not belong to any of the categories that the GDA is related to, or because the item has been already value–enhanced. Afterwards, the GDA tries to exchange the value–enhanced item.
- To exchange first, to value–enhance after (EVE): It follows an equivalent behaviour that in the previous case but changing the

order of the actions.

- The last possible strategy is only to value–enhance (VE), but it does not make sense, because the main aim of the *GDAs* is to get an item from the last range. For this reason, this strategy will not be considered.

- **Devaluation process**: Items lose part of their properties/value over time. A devaluation value (i.e. a substantial drop in the value of an item) is included in the model in order to reflect this natural property. For the owner of the item, the devaluation process is not detectable. For example, if you have an old car and you can travel back and forth without problems, this old car has a level of satisfaction/utility (i.e. PV) optimum or near to the optimum for someone. However, people that are looking for a car may have another rating about your old car. Therefore, each item in the market has a MV for the owner (i.e. MV_{local}) and a MV for the rest of the population (i.e. MV_{global}).

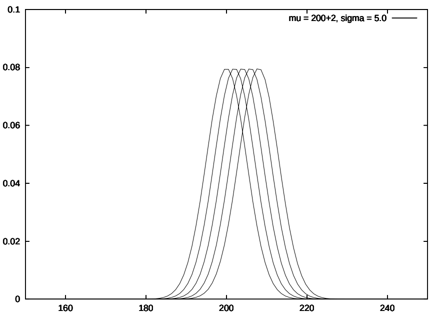
7.2 Implementation Overview

The network modelled is shaped by bidirectional links from GDA's to PA's. A Java simulator is used in order to model different scenarios/experiments.

The simulator follows the model explained in this chapter. For the experiments, the quantity of items per agent is always one. With respect to the items, a low index in the items indicates a low MV and a high index is related to high MV. During the chain of trades it is possible that the PV of the GDA decreases. This is logical because GDA is only interested in the target item which has an infinite value to him. The rest of the items only have value with respect to how useful/valuable they are to the members in the market. The list of issues observed:

Quantity of items and agents: The quantity of agents and items in the market have a great impact on the performance of the market. Finding a profitable exchanges for buyer–seller (i.e. double coincidence of wants) depends on how many members are shaping the market. As the number of agents and items increases, the chances for Kyle also increase.

Range of values: One way to analyse the quantity and distribution of items in the market is in fixed ranges of value – each representing different levels of value and containing multiple items in one range. In a range/level with few items the distance between the MV increases and when the quantity of items increases the distance is reduced. The steps to generate the MV that will compose the market are:



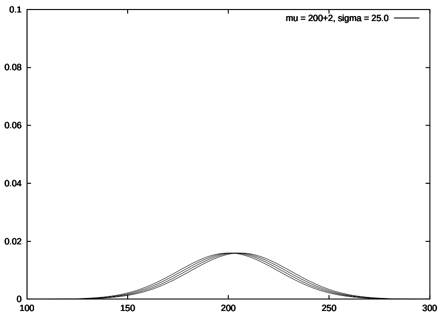


Figure 7.5: a) with $\sigma = 5$ and b) with $\sigma = 25$

1. To establish a range values (i.e. levels of value).
2. To determine a quantity of items in total.
3. To uniformly distribute the items in the range.

The distribution of MV and PV: Figure 7.5 shows a set of five normal distributions where μ_0 is equal to 200 and the following μ's are increasing its value in two units. When the μ value is close, the probability that exchanges can be made is high. With $\sigma = 5$ and $\mu_{i+1} = \mu_i + 2$ the items with which it would be possible to trade is a maximum of seven. However, with $\sigma = 25$ the items for which to trade rises to thirty five. Therefore, the range of MV with which it is possible to make an interchange is greater with $\sigma = 25$ than when $\sigma = 5$. Not that these are only possible trades – since an actual trade still depends on the individual valuations of the agents.

A higher σ increases the quantity of agents to negotiate with and chances of jumping between differently valuables items (i.e. in passing from g_a to g_d where $MV(g_a) \ll MV(g_d)$).

When $\sigma_i = 2$ the P($agent_i \Leftrightarrow agent_{i+1}$) = 0.30 with $\sigma_i = 5$ the P($agent_i \Leftrightarrow agent_{i+1}$) = 0.42. As greater value of σ is the greatest the probability of making an interchange. Also, the number of agents with which it is possible to exchange increases. Following the example and assuming that ($\forall$ a,b $\in$ $items$ $\mu_a = \mu_b + 2$) if $\sigma_i = 2$, the majority of exchanges will be only with μ_{i+1}. However, when $\sigma_i = 5$ the range of agent who exchanges will be μ_{i+1} and μ_{i+2}. Increasing the probabilities of making an exchange.

Neither the distance between MV nor value of standard deviations (i.e. demand/supply) can be changed by any individual in the market.

Figure 7.6 shows normal distributions with $\sigma = 2$ and $\sigma = 5$. In the first case, $P(a > 202.5)$= 0.105 and $P(b < 202.5)$= 0.105. In the second case, with $\sigma = 5$, $P(a > 202.5)$= 0.38 and $P(b < 202.5)$= 0.30. This shows that $\sigma = 5$ with $P(a > 202.5)$ & $P(b < 202.5)$ is greater than with $\sigma = 2$.

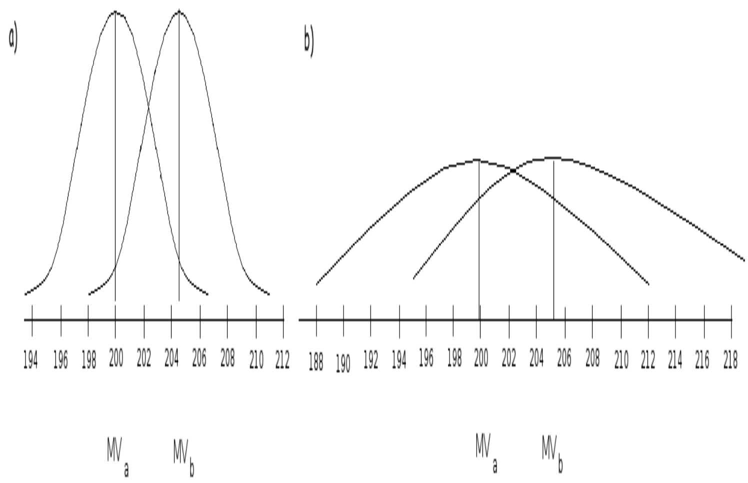


Figure 7.6: Normal distributions with a) $\sigma = 2$ and b) $\sigma = 5$.

In order to arrange realistic experiments, one needs to study the probability of a GDA getting the desired item. In the proposed environment, the GDA has the worst item g_A and the objective is to reach the best item g_Z. The question is "what it are the chances of successfully completing this task?". The first task to consider is to know what the probability of passing from g_A to g_B where $MV_{GDA}(g_B) > MV_{GDA}(g_A)$.

Let, $X \sim \mathcal{N}(\mu_1, \sigma_1)$ and $Y \sim \mathcal{N}(\mu_2, \sigma_2)$. Then $\exists$ an exchange iff the value of the item x_1 is greater than the value of the item x_2 by the node that has x_2. This is equivalent to saying that $\exists$ an exchange iff $\mu_2(x_1) > \mu_2(x_2)$. Finally, it is possible to turn this into equation 7.2.

$$\{P(\mu_2(x_1) > \mu_2(x_2)) = P(\mu_2(x_1) - \mu_2(x_2) \leq 0)\}. \tag{7.2}$$

Due to the properties of the normal distribution and given that X and Y are normal random variables with means μ_1 and μ_2, and variances, σ_1 and σ_2, then:

1. The mean of Y - X = μ_2 - μ_1,
2. The variance of Y - X = $\sigma_2 + \sigma_1$.

Once normalized, the values to a z-score mean we can find the probability that $P(Z < z)$. In this case with z is equal to zero.

In a market it is usual to have many items to exchange. For this reason,there are multiple ways to start with item g_A and reach the item g_Z. In

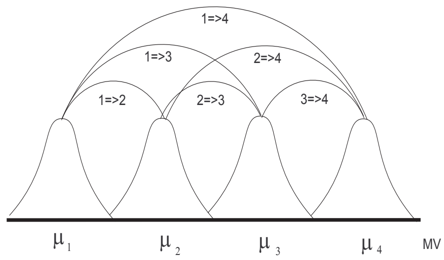


Figure 7.7: All paths from node 1 to node 4 showing the $MV = \mu$ as a set of standard deviations.

Figure 7.7 four items appear; each one with its MV, all of them following a normal distribution.

In this example, the paths from μ_1 at μ_4 by means of exchanges are:

- To exchange x_1 by x_2 ($1 \Leftrightarrow 2$) and afterwards x_2 by x_3 ($2 \Leftrightarrow 3$) and finally x_3 by x_4 ($3 \Leftrightarrow 4$), or

  P(A$_1$) = P(($\mu_2(x_2)$ - $\mu_2(x_1)$) <0) $\cap$ P(($\mu_3(x_3)$ - $\mu_3(x_2)$) <0) $\cap$ P(($\mu_4(x_4)$ - $\mu_4(x_3)$) <0)

- To exchange x_1 by x_2 ($1 \Leftrightarrow 2$) and afterwards x_2 by x_4 ($2 \Leftrightarrow 4$), or

  P(A$_2$) = P(($\mu_2(x_2)$ - $\mu_2(x_1)$) <0) $\cap$ P(($\mu_4(x_4)$ - $\mu_4(x_2)$) <0)

- To exchange x_1 by x_3 ($1 \Leftrightarrow 3$) and afterwards x_3 by x_4 ($3 \Leftrightarrow 4$),

  P(A$_3$) = P(($\mu_3(x_3)$ - $\mu_3(x_1)$) <0) $\cap$ P(($\mu_4(x_4)$ - $\mu_4(x_3)$) <0)

  or

- To exchange x_1 by x_4 ($1 \Leftrightarrow 4$) directly

  P(A$_4$) = P(($\mu_4(x_4)$ - $\mu_4(x_1)$) <0)

No other way exists. Each one of these sequences of exchanges is named an *event*.

The objective is to calculate the probability of all of these events (i.e. P($A_0 \cup \ldots \cup A_n$)). From the basic properties of probabilities (see Eq. 7.3).

$$\{P(A \cup B) = P(A) + P(B) - P(A \cap B)\}. \tag{7.3}$$

Extending to n events in the next equation is obtained:

$$\begin{aligned} P(A_0 \cup A_1 \cup \ldots \cup A_{n-1} \cup A_n) = & \quad P(A_0) + \ldots + P(A_n) \\ & -(P(A_0 \cap A_n) + \ldots + (P(A_{n-1} \cap A_n)) \\ & +(P(A_0 \cap A_1 \cap A_2) + \ldots + P(A_{n-2} \cap A_{n-1} \cap A_n)) \\ & -/+ \ldots -/++P(A_0 \cap \ldots \cap A_n). \end{aligned}$$

To simplify the formulation of the union of n events, let E_α (α = 1, 2, . . . , n) be Eq. 7.4.

$$\{P(\bigcup_{\alpha=1}^{n})E_\alpha = \sum_{\alpha=1}^{n} P(E_\alpha) - \sum_{\beta>\alpha=1}^{n} P(E_\alpha \cap E_\beta) + \ldots + (-1)^{n-1} P(E_1 \cap \ldots \cap E_n)\}. \tag{7.4}$$

Given that the events are independent then Eq. 7.5:

$$\{P(\bigcup_{\alpha=1}^{n})E_\alpha = \sum_{\alpha=1}^{n} P(E_\alpha) - \sum_{\beta>\alpha=1}^{n} P(E_\alpha)P(E_\beta) + \ldots + (-1)^{n-1} P(E_1) \ldots P(E_n)\}. \tag{7.5}$$

Where n is the quantity of different events. And P(A_0) is the probability that the event A_0 happens. And where P($A_0 \cap A_1$) is the probability that the events A_0 and A_1 happen. In order to simplify the calculation of the equation 7.5:

$$\begin{aligned} P(A_1 \cup A_2) = & \quad P(((\mu_2(x_2) - \mu_2(x_1)) < 0) \cap ((\mu_3(x_3) - \mu_3(x_2)) < 0) \cap \\ & ((\mu_4(x_4) - \mu_4(x_3)) < 0) \cap \\ & ((\mu_3(x_3) - \mu_3(x_1)) < 0) \cap ((\mu_(x_4) - \mu_4(x_3)) < 0)) \equiv \\ & P((\mu_2(x_2) - \mu_2(x_1)) < 0) \cap P(((\mu_3(x_3) - \mu_3(x_2)) < 0) \cap \\ & ((\mu_3(x_3) - \mu_3(x_1)) < 0)) \cap \\ & P(((\mu_4(x_4) - \mu_4(x_3)) < 0) \cap ((\mu_4(x_4) - \mu_4(x_3)) < 0)) \equiv \\ & P((\mu_2(x_2) - \mu_2(x_1)) < 0) \cap P(\mu_3(x_3) < min\{\mu_3(x_2), \mu_3(x_1)\}) \cap \\ & P((\mu_4(x_4) - \mu_4(x_3)) < 0) \approxeq \\ & P(\mu_2(x_2) - \mu_2(x_1) < 0) P(\mu_3(x_3) - \mu_3(x_1) < 0) \\ & P(\mu_2(x_2) - \mu_2(x_1) < 0) \end{aligned}$$

The final task is to calculate how many paths exists from g_A to g_Z. The approach, in our case, to thinking of the paths form g_A to g_Z as a tree. Where

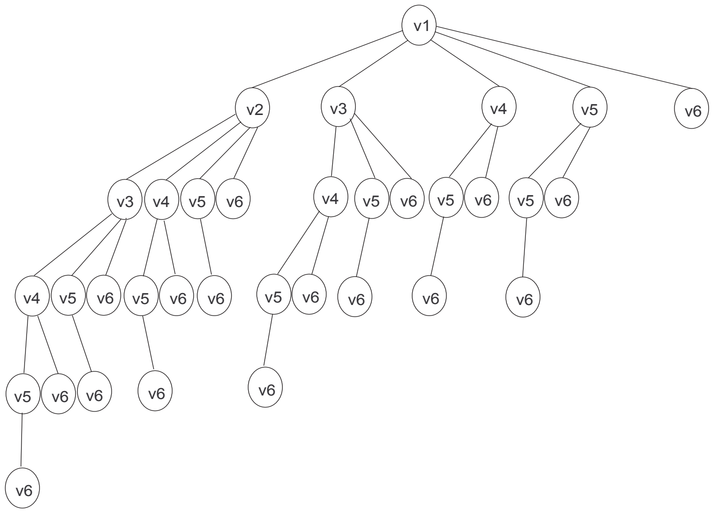


Figure 7.8: All paths from node 1 to node 6 showing as a tree.

the root is the g_A and the following items in an increasing order shape the tree. And the lowest are the g_Z items. Figure 7.8 follows this approach showing the all paths with six items in the market. Taking the root of the tree to be the GDA with the item$_1$, the rest of nodes are PA's. The leaves are the best items in the market. In order to count the quantity of paths between two items was defined the recursive function in Algorithm 5. With minimum changes this function can provide one–to–one the paths from the root to the leaves.

Algorithm 5 Function counting(index, index$_s$, index$_d$) to count all paths between two nodes

$value \Leftarrow 0$
if $index$ is $inxed_d$ **then**
  $value \Leftarrow 1$
else
  for $i = index + 1$ to $index_d + 1$ **do**
    $value \Leftarrow value + counting(i, index_s, index_d)$
  end for
end if
$value$

The cost to create all paths is computationally explosive:

- With 10 items $\Longrightarrow$ 255 paths $\Longrightarrow$ 1,280 entries (i.e. $\mu_a \Rightarrow \mu_b$)

- With 15 items $\Longrightarrow$ 8,190 paths $\Longrightarrow$ 58,847 entries (i.e. $\mu_a \Rightarrow \mu_b$)
- With 20 items $\Longrightarrow$ more than 110,000 paths $\Longrightarrow$ more than 1,200,000 entries (i.e. $\mu_a \Rightarrow \mu_b$)

This limitation only has allowed to work with 10 or 15 items. The ranges for the MV were 25, 50 and 100. The scenarios and results obtained are in the table 7.1. Being many of these paths are redundant.

	$\alpha = 2$		$\alpha = 5$		$\alpha = 10$	
range/items	10	15	10	15	10	15
25	0.0011	0.026	0.81	$\simeq 1$	$\simeq 1$	$\simeq 1$
50	1.69E-10	8.91E-8	0.01	0.19	$\simeq 1$	$\simeq 1$
100	$\simeq 0$	2.21E-22	0.968E-8	1.45E-5	$\simeq 1$	$\simeq 1$

Table 7.1: Scenarios with σ = 2, 5 and 10 with different ranges.

Two different probabilities are related to this model based on ranges:

- **Inter–range:** The probability of reaching the desired object starting with the chain of trades from the worst item (i.e. from $range_0$ to $range_N$). This is a binomial random variable, a random variable that counts the number of successes in a sequence of independent Bernoulli trials with fixed probability of success. In our case, the probability of passing to the next range (i.e. of having a successful jump or not).
- **Intra–range:** This corresponds to the probability that a GDA finds a PA to interchange the items in the next range.

Inter–range: The model follows a probability distribution of binomial random variable. In the model, success happens when the GDA pass from a $range_i$ to a range $range_{i+1}$.

In a scenario when the success rate is measured at 80% [14] (i.e. in the 80% of the cases exists an agent in the upper range that is more interested in the item offered by the GDA than in the ownership). Thus, p = 0.8 and 1-p = 0.2. Taking n = 100 items. The probability of getting 100 successful jumps is in equation 7.6.

$$P(X = 100) = f(100; 100, 0.8) = 2.03e - 10 \tag{7.6}$$

Intra–range: In a range the most important variables are the quantity of items, the distribution and the standard deviation of the PV, assuming

[14] The probability to jump from a range_i to a range_{i+1} is independent of the range.

that a range has a fixed PV and that the PV follows a uniform distribution in this range. Let, $X \sim \mathcal{N}(\mu_1, \sigma_1)$ and $Y \sim \mathcal{N}(\mu_2, \sigma_2)$. There exists an exchange iff the value of the item x_1 is greater than the value of the item x_2 by the node that has x_2. This is equivalent to saying that $\exists$ an exchange iff $\mu_2(x_1) > \mu_2(x_2)$. This will be characterized by the event E. In this case the scenario has one agent that has an item μ_1 and n agents that have items in μ_2. The objective is to set a bound k, as is showed in equation 7.7.

$$\{P((\mu_2(x_1) > \mu_2(x_{\alpha=1..n})) = k) = P(\sum_{\alpha=1}^{n} P(E_\alpha))\}. \tag{7.7}$$

This is the probability of passing from the item with a MV of μ_1 to the item with MV equal to μ_2 has a value k. The table 7.2 shows the quantity of items that are necessary in order to reach probabilities of 0.2, 0.5 and 0.8 working with a range of standard deviation from 2 to 5.

	P = 0.2		P = 0.5		P = 0.8	
	μ_2-μ_1=7	μ_2-μ_1=20	μ_2-μ_1=7	μ_2-μ_1=20	μ_2-μ_1=7	μ_2-μ_1=20
σ=2	860	$\simeq \infty$	2,149	$\simeq \infty$	3,438	$\simeq \infty$
σ=3	21	$\simeq \infty$	51	$\simeq \infty$	82	$\simeq \infty$
σ=4	5	666,252	13	1,665,630	20	2,665,008
σ=5	3	6,292	7	15,729	10	25,166

Table 7.2: The quantity of items that are necessary in each scenario in order to reach a P = 0.2, P = 0.5 and P = 0.8.

The standard deviation σ splits the simulations into two graphs (see Figure 7.9). When σ is equal to two and when this σ is equal to five. The σ is related to the variation of taste that the agents have with respect to the value of an item The y–axis shows the distance between a pair of items. This distance is equal for each item in the market. The four different scenarios are when the distance has a value of 5, 10, 15 and 20. Along the x–axis, each column is the mean value of the range. The mean is taken from one hundred simulations. The legend shows the quantity of items that are involved in the scenario. Three quantities of items are studied: when the market has 420,000, 42,000 and 4,200 items. In all the simulations we work with one hundred ranges (i.e. levels of price for the items). The GDA starts with an item that is in the $range_0$ and wants an item that belongs to the $range_{100}$. The results obtained clearly shows behaviour according to the these parameters, quantity of items, σ and distance, as follows:

- As the quantity of items in the market increases, more ranges/levels can be added.

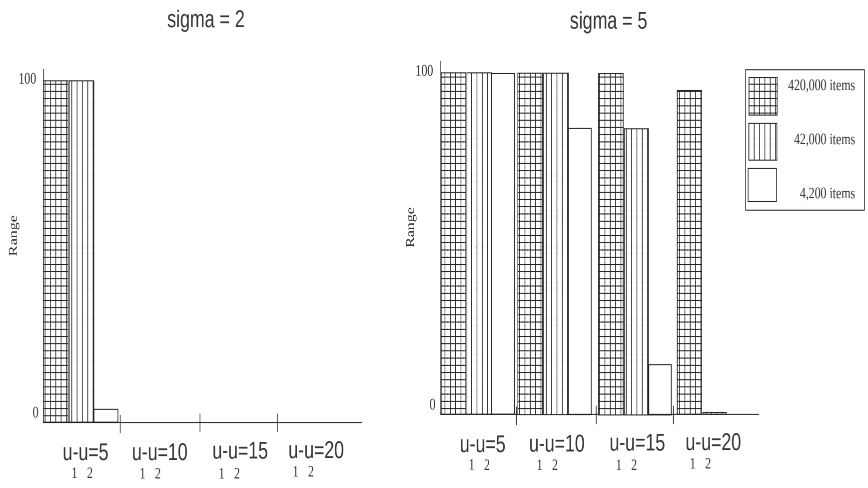


Figure 7.9: Mean value of the range obtained when a) $\sigma = 2$ and b) $\sigma = 5$

- A larger σ should increase the value of the range.
- The standard deviation (i.e. the dispersion of a collection of numbers) reveals as an item has a range greater value, the item will be easier to exchange.
- The distance between ranges reveals that no one is interested to turn a non valuable item into a valuable item (ex. a pen into a car).
- The few items to exchange in an upper range there are, the probability to exchange decreases.

The graph shows that with a σ equal to 2 it is only possible for a goal driven agent to make trades when the distance is equal to five or lower (i.e. the distance between MV is lower than five). Focusing on this scenario, when μ_2 - $\mu_1 = 5$, the results show the relevance of the quantity of items. With 420,000 and 42,000 items, the range obtained over one hundred different simulations the range obtained maximum is $\equiv$ GDA reaches the targeted item. But when the quantity of items is reduced to 4,200 items it is not true. In this case the mean value is 1.2.

The maximal length of the chain of trades was seven. The reason to this low value is because as the number of items is reduced, the chances of jumping from one level to another reduce. Concretely when σ is equal to 5 with μ_2 - $\mu_1 \leq 5$, the GDA always gets the desired item. In this scenario is independent the quantity of items that the market has. Figure 7.9 shows that when μ_2 - μ_1 = 5 and σ equal to 5, a GDA gets the item of upper range with 420,000, 42,000 and 4,200 items.

In the rest of scenarios, a greater distance implies smaller ranges. Increasing the distance between MVs the value of the range obtained decreases. Comparing graph 7.9 a) and b), we can compare what effect σ has on the range obtained. The results obtained with $\sigma = 5$ are better than when $\sigma = 2$. The results show that:

- Certain configurations assure the best value of the range (e.g. $\sigma = 5$ and μ_2 - μ_1 = 5)
- Certain configurations lead to the worst value of the range (e.g. $\sigma = 2$ and μ_2 - μ_1 = 10)
- The quantity of items, σ and distance has a deep impact in the results. But none of these parameters can be managed by an unique agent, these parameters are provided by the market.
- The Kyle's scenario is one where the quantity of agents tends to infinite. This ensures that the probability of finding out an item that allows passing to an upper range increases. The problem is to contact with the right person that has this item that GDA needs.

Distribution of *GDAs*:

- **One *GDA*:** The most basic form of the systems to be explored is that in which there is only a single GDA looking for a desired item which has the highest value in the market.

  The probability of turning an item from range$_x$ into an item of range$_{x+1}$ depends on the quantity of items per range, the quantity of ranges, the range of PV and the distance between ranges associated to MVs.

  When the quantity of items per range is near to zero, P(success) will be zero. At the other extreme, when the quantity of items per range tends to infinity, P(success) tends to be one. Figure 7.10 a) shows the effect of the quantity of items per range. The only two parameters modified are: the quantity of items per range and the distance between ranges. The rest of the parameters are fixed. Simulations are related to the case where the distance between the lower range and the higher range is equal to fifty (i.e. fifty hops are necessary to transform a paperclip into a house) and the range of PV is equal to five. The figure shows that as there are more items per range there are more probabilities that the GDA will reach the last range and thus more access to the most valuable items. Also the figure shows that in some configurations (for example – with few items per range as 10 items x range), the probability of reaching the last range is near to zero. And in other configurations, for example with 1,000 items x range, a range of PV equal to 5 and a distance between ranges equals to 2, this probability is high but not 1 – in this case 0.82.

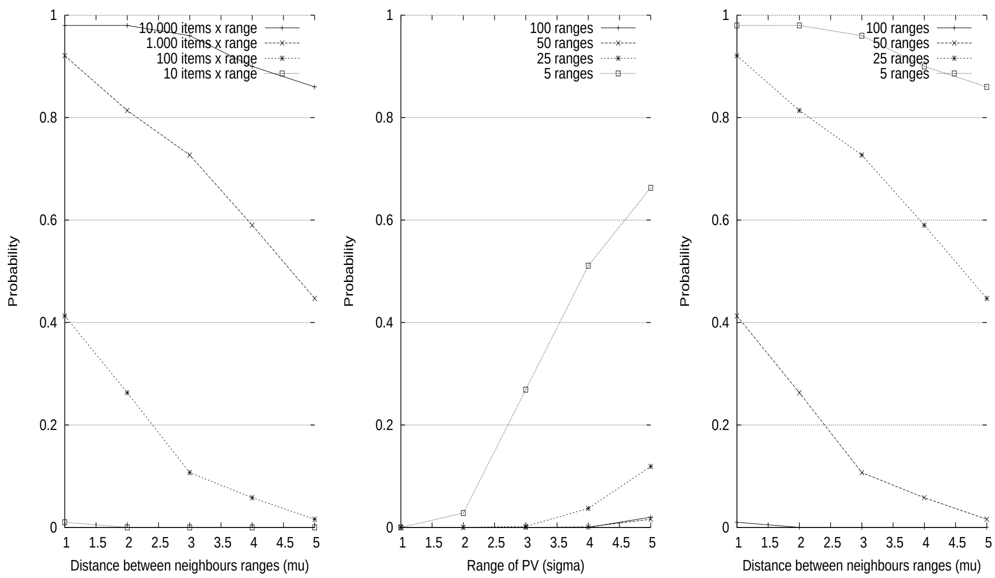


Figure 7.10: Results related to the parameters in the simulator a) items per range and distance between ranges b) quantity of ranges and variations of PV, c) quantity of ranges and distance between ranges

Figure 7.10 b) shows different variations of PV from 1 to 5 and the quantity of ranges. The rest of parameters are: quantity of items per range is 1,000 and the distance between ranges is equal to 5. Increasing the value of PV the probability of reaching the last range increases.

Finally, Figure 7.10 c) shows the effect of the distance between ranges combined with the quantity of ranges. The probability of reaching the last range decreases as distances between ranges increase or the quantity of ranges increases. The variation of PV is fixed to 5 and the quantity of items per range is equal to 1,000. As the number of ranges to cross over is lower, it is easier to reach the last range. It could be noted that as the distance decreases between ranges it becomes easier to get an item from the last range.

The statement shows that GDA can turn an item from the initial range to the last range with a high probability of success under many configurations such as with a distance between ranges from 0 to 2, with more than 1,000 items per range with a $\sigma > 4$ and where the number of ranges are those included between 25 and 50 ranges. The probability of reaching the last range is close to one. Furthermore, this probability is completely independent of altruism. Because, by definition, neither GDAs nor PAs accept any detrimental trade.

- **Multiple *GDAs*:** Social insects tend to arrange items in their surroundings according to specific criteria, e.g. broods and larvae sorting in ant colonies. This process of collectively grouping items is commonly observed in human societies as well, and serves different purposes, e.g. garbage collection. Once proven that an isolated GDA can reach an item from the last range under some configurations, the next step is to balance the quantity of PAs and GDAs, to check the behavior of the market with other distribution populations. Therefore, the strategy is to increase the percentage of GDAs in the market in order to reveal the dynamics that appears in front of the variation of populations.

  The set of experiments uses configurations with a percentage ranged from 0, 0.02, 2, 10, 20, 30, 40, 50, 60, 70, 80, 90 to 100 % GDAs. Other parameters are set as follows: the variation of PV is equal to five, the distance is equal to five (i.e. difference between two consecutive MV). These parameters are chosen from the previous section because they form a fruitful environment where trades with one GDA can be made. These results are presented in Figure 7.11 where the quantity of crossed ranges or jumps is shown with respect to the percentage of GDAs. The solid line is related to the maximum sum of jumps. This value captures starting from a random distribution of the GDAs in the different ranges, how many crossed ranges should be crossed to become this initial situation in a situation where all the $GDAs$ have the best available items. On the other hand, the dotted line is related to the sum jumps that were obtained by simulations.

  Focusing on this later value, the figure shows that when the percentage is reduced (i.e. less than 2 %) the value of jumps in our simulator and the maximum value expected is equal. The best results with respect to the quantity of crossed jumps are achieved when the balance of GDAs is around 10 %. The reason is because many GDAs are making jumps but not enough to decrease the opportunities to make exchanges from the rest of GDAs in the market. Under other configurations this property

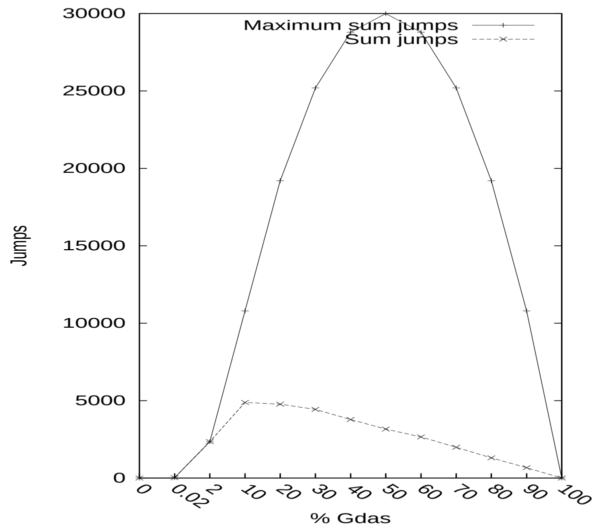


Figure 7.11: The mean range value decreases as quantity of GDAs increases.

is not applicable. As the quantity of GDAs increases in the market the sum of jumps go down slightly. At first glance, more GDAs in the market should implies that more jumps could be done, the problem is that the opportunities of jumps decreases, ending up with the opposite of the expected value.

As the number of GDAs increases, it is more difficult to make trades between agents. The reasons are:

- As great the distribution of GDAs is less probably to have an encounter with a PA.
- Once a PA makes a trade the following events occur:
  * The PA increases its PV.
  * The PA moves downwards by one range.

Unsurprisingly, GDAs with an item near to the last range (i.e. rich agents) tends to obtain better results than GDAs with an item far from the last range.

- To be far from the last range implies more jumps between ranges. The probability decreases when more jumps need be made to reach the last range.
- GDAs share a common goal. They try to move upwards and the competition amongst GDAs increases. The displacement of GDAs

in the ranges of the market takes place, from an initial uniform distribution in the initial step to an n–shape once the simulation runs. In this last figure we can observe how GDAs are gathered in the upper ranges making the swap more competitive between these ranges

 – GDAs near to the last range trade with PAs that allow to get upper ranges. Once these PAs have made a trade it will be more difficult for the next GDAs to offer an useful item.

At a large–scale, the inclusion of GDAs turn a fruitful market into one without hardly any opportunities. With lower levels of GDAs (i.e. less than 10 %) the GDAs can turn into best ranges. But once passed 10 %, the opportunities to improve decrease and changes to get the desired item disappear quickly.

These results show a decreasing refund in contrast of when the market has an isolate GDA that the competition among GDAs reduces the chances to reach the desired item.

Using backtracking: The objective in this section will be to compare and contrast results using BT and without BT. Backtracking algorithms try each possibility until they find the right one. It is a depth-first search of the set of possible solutions. During the search, if an alternative does not work, the search backtracks to the choice point, the place which presented different alternatives, and tries the next alternative. When the alternatives are exhausted, the search returns to the previous choice point and tries the next alternative there. If there are no more choice points, the search fails.

Without backtracking, the process is to search for a unique path between range_0 and range_N. Adding backtracking, the algorithm will always find the solution if the solution exists, because the algorithm explorer all possible paths between range_0 and range_N. The problem of brute force is that the cost is proportional to the number of paths. One solution could be to limit the space search, stopping the backtrack process when the gap between the upper and lower bounds becomes smaller than a certain threshold. This can greatly reduces the computation required with brute force. Other option is to include a *heuristic*. An heuristic $h(n)$ estimates the expected utility of the game from a given position. Heuristic search algorithms typically take the form of traditional algorithms, modified to make intelligent decisions when choosing which path to travel first. The heuristic is a *rule of thumb* that is used to steer the algorithm in a direction that seems more likely for the given problem. These algorithms are useful in intelligent agent systems.

The problem in this case is to determine how the heuristic function knows whether or not an item is better? Better meaning that with this item the agent will get an item from the last range. A good heuristic is one that can detect the path from an initial range to the last range. In our problem any heuristic could be applied because an agent$_i$ in a range$_j$ only can know the exchanged item in range$_{j+1}$ could be interchanged in range$_{j+2}$ once the agent$_i$ has the item from range$_{j+1}$. Making a parallel with the well–known heuristic to know if in a path of cities we are closer or farther each time by the distance between the city where the agent is and the destination city. In our case, the problem is that the heuristic could know that an upper range is better than a lower range, because the agent is closer to the last range. However, it could be that in a range the agent stays is a no way out state. And this state is not detected until the agent reaches this range.

Figure 7.12 shows the mean range obtained when the GDAs work with BT limiting the search to k=2 and without BT. The parameters remain as in the previous configuration. Except for the range of PV that turns his value from 5 into 2. With this change, opportunities to pass from a range to the upper range are reduced. When a percentage of $GDAs$ which is above 10 %, the BT no longer is a benefit but has become detrimental to performance.

BT algorithm reaches the maximum ranges when the percentage of GDAs is lower than 0.5 %. From 0.5 % to 2 % the BT algorithm gets best results than when the agents are not working with BT. However in this range the BT algorithm does not reach the maximum ranges. The reason is due to the destructive nature of the search. From the rest of scenarios the BT algorithm worse the results.

Surprisingly, the BT algorithm does not improve the performance. The main reason is because the search process is destructive (i.e. making upward and downward exchanges the environment changes), in terms of changes the state of the market. The PAs become more demanding with each exchange (i.e. reducing the marginal utility). In the initial exchanges PAs have a wide range of values to exchanges (i.e. from $PV_{pa(x)}$ to $MV_{x+1} + \sigma$) where the PA will accept an exchange. But during the simulations the PAs exchanges its item by means of upward and downward exchanges and the range of items interesting from the PA decreases. Following with results from Figure 7.12, with 0.5 % GDAs and BT around 890 exchanges are made instead of 297 without BT. Obviously, BT increases the quantity of trades because the search process BT looks for other exchanges instead of stopping as in the original approach. However, when the market has 1 % GDAs the trades are 2,484 with BT with respect to 477 without BT. The growth of trades is not supported by the market affecting to the performance.

The effect of an individual or few individuals in a population is insignif-

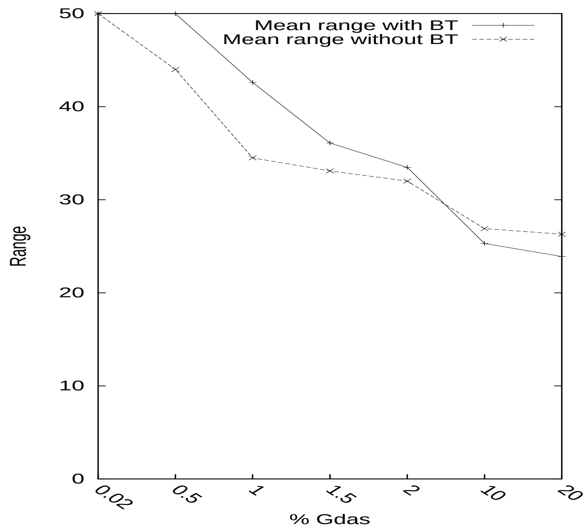


Figure 7.12: The mean range with BT and without BT.

icant because although the trades are reducing, the marginal utility from some PAsv others PAs are available in the population to deal. But when the quantity of GDA is high, the destructive process eliminates the possible benefit that the BT algorithm provides. Therefore, the results show that when the quantity of GDAs is limited, the BT gets better results. But once the market is plenty of GDAs differences between working and not working with BT are negligible.

Interaction with the environment: Each exchange has an effect on the environment. $GDAs$ exploit PV differences from the PAs. In each exchange, two participants want to improve their own payoff, increasing PV for PA and MV for GDA. Once the exchange has been made, the GDA improves its MV and the PA improves its PV. For every future exchange it will become increasingly more difficult for a new GDA to achieve an exchange with this PA. In fact, in each exchange the PA will be more demanding. Therefore, it is more complex for $GDAs$ to trade with a PA that has made many exchanges than with another PA that has not made any previous exchanges. The next task is to consider how the strategy has more effect in the environment/market in terms of PV_{PA} changes.

In VEE from a range$_j$ to range$_k$, MAX = MIN (see equation 7.8):

$$\{\sum_{i=j}^{k}(IV + PV_{PA}(item_{GDA})) - PV_{PA}(item_{PA_{i+1}})\}. \tag{7.8}$$

In EVE from a range$_j$ to range$_k$, MIN (see equation 7.9):

$$\{\sum_{i=j}^{k}(PV_{PA}(item_{GDA})) - PV_{PA}(item_{PA_{i+1}})\}. \quad (7.9)$$

In EVE from a range$_j$ to range$_k$, MAX (see equation 7.10):

$$\{\sum_{i=j}^{k}(IV + PV_{PA}(item_{GDA})) - PV_{PA}(item_{PA_{i+1}})\}. \quad (7.10)$$

Thus,

- Minimum $VEE >$ Minimum EVE
- Maximum $VEE =$ Maximum EVE
- Maximum and minimum $E =$ Minimum EVE

Combining value–enhancement and devaluation: Figure 7.13 shows a scenario where the devaluation process with the past of time is revealed. Figure a) and b) without value–enhance action and c) and d) with value–enhance action. In this case, the obvious expected result is that $GDAs$ that can value–enhance items will get better results than $GDAs$ that can not value–enhance. In a market where the items devalue (Figure 7.13 a) and c)) their value for the rest of members, without value–enhance action, the $GDAs$ only are determined to exchange when the item is not very devaluated. Once the item has been devalued, the item is not valued by the $GDAs$ in the market. When $GDAs$ can value–enhance the items the opportunities to exchange items are greater.

Figures 7.13 b) and d) show the state when an item has suffered a deterioration. In b) the $GDAs$ with a MV better than $MV_{\text{CLASS ITEMS}_1}$ want not to offer anything to the PA with the item$_1$. Also the $GDAs$ with a lower $MV_{\text{CLASS ITEMS}_1}$, but near to this value, want not to exchange with the PA because MV_{item_1} is lower than MV for these $GDAs$. Finally, the $GDAs$ with a lower MV_{item_1} cannot exchange with the PA because for these $GDAs$ will be very unlikely to offer an item to PA better than item$_1$ because the distance between $MV_{PA}(item_1)$ and $PV_{PA}(item_1)$ and the item that can offer these $GDAs$ is too far. In d) where it is possible to value–enhance the items, the pattern of exchanges is similar to the previous scenario with the difference that the $GDAs$ with a MV between $MV_{\text{CLASS ITEMS}_1}$ and MV_{item_1} can exchange with the PA provided that the value–enhance plus MV_{item_1} will be upper to the MV of the GDA that want to make the exchange.

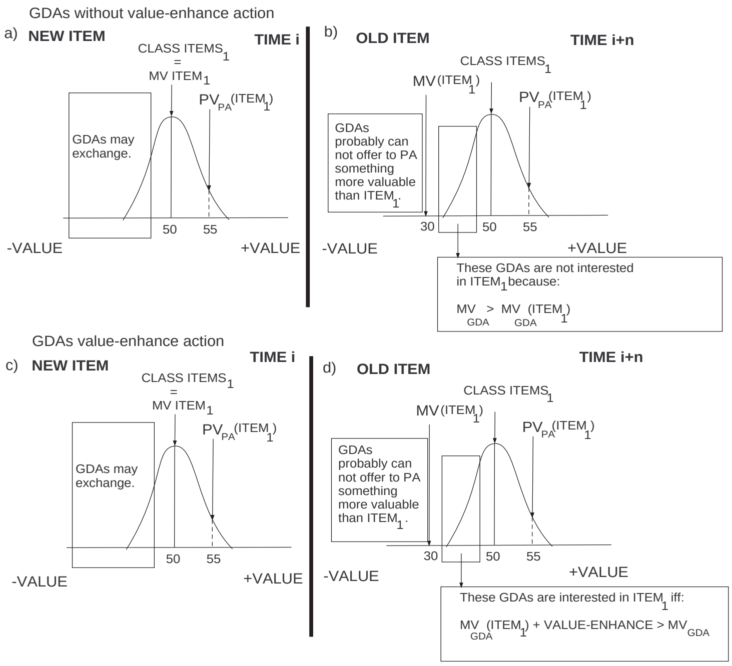


Figure 7.13: Forecasting scenario mixing value–enhance action and the devaluation process.

7.3 Experiments

7.3.1 Experimental Configuration

Bringing together descriptions of the problems from the previous section, the high level properties of the model are the following:

- Initially, items are randomly assigned to agents. One item per agent.
- The number of ranges is fifty. Each range is composed of one hundred items. In $range_1$ there are the items with smaller value and in the $range_{50}$ the items with the higher value.
- *GDAs* know where the rest of the agents are.
- Items have a unique MV but each agent has its PV for each item in the market.
- The number of categories is equal to 10.
- The quantity of categories where a GDA belongs are 2 or 8.
- The simulator offers the opportunity to make an action per cycle. An agent can either value–enhance or exchange an item. Once, the *GDAs* select an action it should wait until the next activation cycle returns in order to make a new action.
- The market has 500 *GDAs* and 4,500 *PAs*.
- Each agent has an item, thus the market has 5,000 items.
- The *improved value* (IV) the difference between the original PV item and the value–enhanced item, is equal to 2 or 5.
- The *devaluated value* (DV) the depreciation between the MV_{local} and MV_{global}.

7.3.2 Easy/Difficult Environments

Simulations show the outcomes of the strategies when the market favours and does not favour the trade. In the easy environment, a GDA has a high probability of success, near to 90 % (i.e. to turn an item from initial $range_x$ into an item from the last range) is seen. On the contrary, in the difficult environment the probability to success decreases to below 40%. For the easy environment the standard deviation is equal to 5 and in the difficult environment is equal to 2.

Value–enhance–action: In this case, *GDAs* can improve the items that they have. Figure 7.14 shows the performance in terms of quantity of value–enhancements and jumps of the two environments. On the x–axis we see the strategies studied, followed by two numbers A_B. A is the IV and B is the quantity of categories where the GDA belongs to.

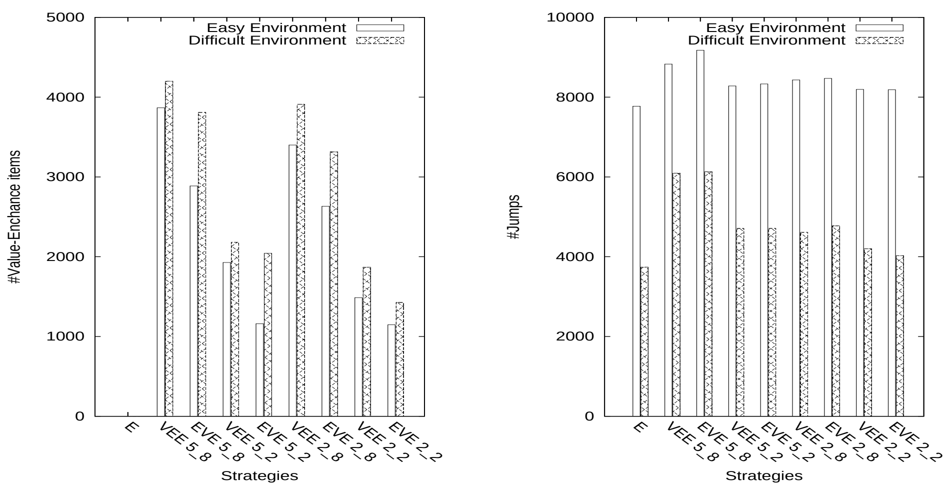


Figure 7.14: Comparing the easy and difficult environment in terms of: a) Quantity of value–enhancements and b) Quantity of jumps.

The following results were obtained:

- As was presumed, the easy environment get better results with respect to the difficult environment in terms of jumps (i.e. a jump is an exchange between a GDA and a PA. The result is that GDA gets an item from an upper MV than before the exchange). However, the quantity of value–enhancements made is large in the difficult environment. With more jumps, more value–enhancing should be done. But in the easy environment it is likely to exchange a value–enhanced item whilst this does not usually happen in the difficult environment.
- Comparing the strategies, E gets the worst results. Both strategies VEE and EVE get similar results but the last one is a little better.

In any case, to value–enhance items improves the global market performance.

- The greater quantity of items the GDA can repair the probability of achieving.

- Focusing on VEE and EVE strategies, as great IV and the more quantity of items that a GDA can value–enhance the better the results are.

- In the easy environment, the distance in jumps between E and VEE or EVE is not significant. It is due to the fact that the easy environment is favourable to making exchanges. However, in the difficult environment, the PAs have a more demanding criteria at the moment to make exchanges. In this case, to be able to improve the value of items is an advisable advantage. However, when the quantity of categories or value–enhance is not enough, the improvement to work with any value–enhance strategy is not too evident. When the quantity of categories is low in a difficult environment.

- A GDA with a value–enhancement that tends to ∞ and is able to improve any item, always gets to the last range. However, these assumptions are not very realistic.

Value–enhance–action and devaluation process: Figure 7.15 shows the performance in terms of quantity of jumps of the two environments, the first Figure shows the easy environment and the second one the difficult environment. Were studied the case where $DV = 2$, 4 and 6, with $IV = 5$ and the $GDAs$ can improve items belongs to 8 categories.

The following results were obtained:

- The greater the DV, the worse are the results.

- The most relevant issue is the strong difference between repaired strategies (i.e. VEE and EVE) and strategy E. Without value–enhancing actions present, once an item is devalued, it is not recoverable for the market (i.e. it will never again be traded). However, with value–enhancing action, and if the IV has a value similar or upper to the DV, it is available to do exchanges.

- When the IV is significant lower than DV or when the quantity of categories related to the $GDAs$ is lower the results that get the simulator are far to the optimal.

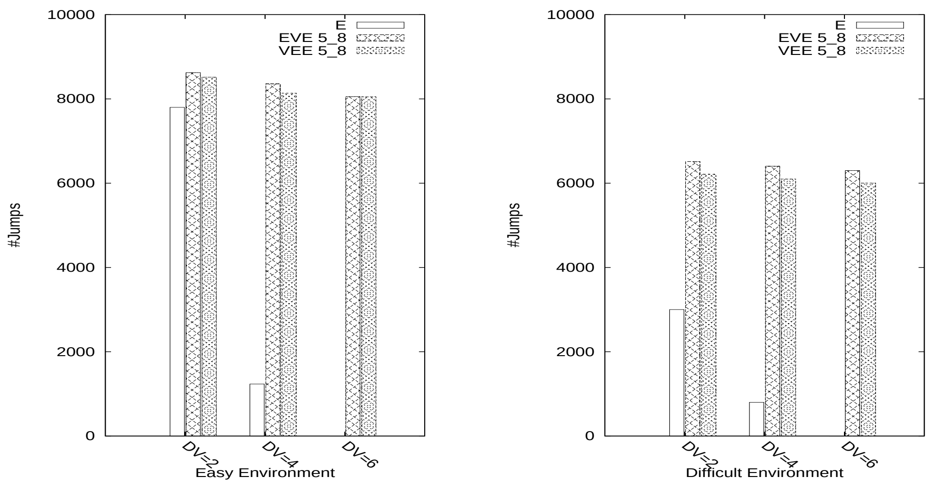


Figure 7.15: Comparing easy and difficult environments in terms of quantity of jumps.

Comparing the quantity of jumps in Figures 7.14 and 7.15 both the easy and difficult environment and focusing on 5_8 without value–enhance action show that with devaluation process is the quantity of jumps reduced significantly. However, the value–enhance action does not change the quantity of jumps.

7.3.3 Mixing Strategies

The aim of these second series of experiments is to compare the performance of the strategies proposed dividing the population by the strategy. We evaluated the following mixed strategies under the difficult environment outlined above:

- Half of the population follows a VEE and the other half an EVE strategy.
- Half of the population follows a VEE and the other half an E strategy.
- Half of the population follows an EVE and the other half an E strategy.

Value–enhance–action: From Figure 7.16 the following results were obtained in a difficult environment:

- Strategy EVE is slightly better than VEE.
- Strategy E is a weak strategy in with respect to the rest of strategies. $GDAs$ that follow EVE or VEE trade up more quickly to ranges, closing opportunities to the $GDAs$ that follow strategy E. EVE closes paths of trade more quickly than VEE.
- As worse results are obtained in strategies VEE and EVE strategy E gets the best results.

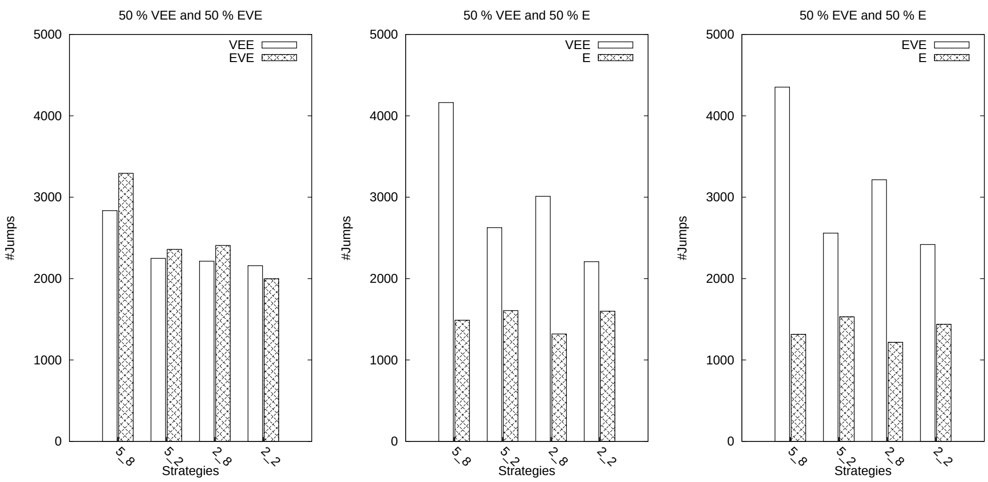


Figure 7.16: Quantity of jumps in mixing strategies with a) 50 % VEE and 50 % E, b) 50 % VEE and 50 % E and c) 50 % EVE and 50 % E.

Value–enhance–action and devaluation process: From Figure 7.17 the following results were obtained with 5_8 in a difficult environment:

- Strategy EVE is slightly better than VEE.
- The differences between value–enhance strategy and non–value–enhance strategy are highlighted by mixing these strategies.

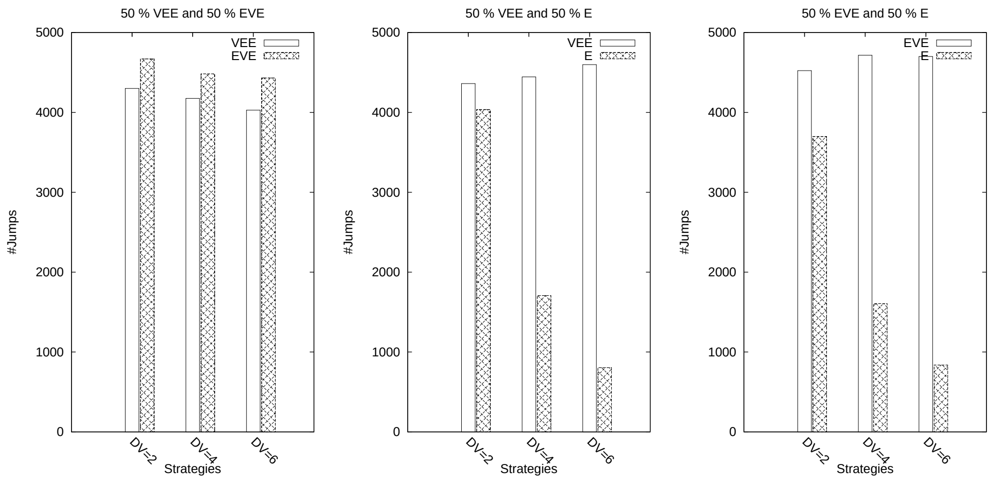


Figure 7.17: Quantity of jumps in mixing strategies with a) 50 % VEE and 50 % E, b) 50 % VEE and 50 % E and c) 50 % EVE and 50 % E.

Comparing the quantity of jumps in Figures 7.16 and 7.17 focusing on 5_8 scenario with devaluation the different between value–enhance strategy and non–value–enhance strategy are evidence. The E strategy against VEE or EVE strategy gets best results when the devaluation process is not present.

In the modelled market, there are sequences of trades that turn an item from range$_x$ into an item of the highest range. However, a number of conditions need to be met in order for GDAs to be able to make these trades and in particular the following parameters are of relevance:

- **The distance between MVs:** As this distance increases it is more difficult to change an item – with increasing gaps between valuations.
- **The variance of PV:** The greater the variance in the PV, the greater the probability that a PAs will be interested in to interchanging items – since some outliers will have very high valuations.
- **The quantity of items per range:** A market where the quantity of items is great will increase the possible chains to reach the target item.
- **The quantity of ranges:** The fewer the ranges the easier it is for

GDAs to have access to the last range where the desired item resides. In fact this parameter varies with the distance between ranges.

- **The quantity of GDAs in the market:** The more GDAs there are, the more competition there is since many GDA may be trying to get the best items in the market. On the other hand, the quantity of PAs increases the opportunities to trade up by the GDAs.

Observing the results obtained with the simulator, we can address to the questions proposed in the initial part of the paper:

- What conditions are necessary in the market in order to have satisfied agents (i.e. goal driven agents obtain the item that they want)? The cartesian coordinates that have been studied in this paper with respect to the variability in the model are:
  - The quantity of ranges and the distance amongst the ranges.
  - The quantity of items and the distance amongst the PV of the items.
- How does the goal driven agent (GDA) know that an exchange gets them closer to their dream? When it has finished a trade any GDA knows that the MV of the new item is better than the old one. This information is useful because at the level of prices, the opportunities to reach a flat increases if the item that you have has a near value to the value of the house. But the internal preferences associated to the members in the market are not known by the GDA. This unrevealed information makes turn into *blind search* the fact to know how much it is interested in that. Moreover the model proposed assumes that the GDA has a link to any member of the market a few probable real scenario. Assuming this limitation, the usual strategy of the GDA's accustoms to follow diffused objectives.
- How many GDA's can achieve their dreams? Including more than on GDA in the market is like including rival agents. When the others GDA are nearer to the targeted items is because they have interchanged with other agents. During this process the GDA takes profit of the marginal benefit. This is that the marginal benefit have been totally or partially consumed in the transaction, being more complex for the previous agents reach their targeted items due to the marginal benefit (i.e. the change to make a trade) has decreased. This environment will be face with these issues:

- The fact of having more than one GDA in the market could be realized by the PA's. With the knowledge of the demand the PA's can impose the price most beneficial to him.
- With more than one GDA in the market coalitions of these agents could appear in order to reach their desired items.

Because the value of material things is subjective. People base the value that they place on any good or service on the satisfaction that they expect to derive from it. Parties trade with one another because each one expects to gain more satisfaction from what he obtains than from what he gives up.

People value things differently, in part because people just have different values but also because of marginal utility. Marginal utility is just the idea that the value to you of something is based on the value of getting it in addition to what you already have. e.g. if you already have enough food to eat, you might not value extra food as much. A second car is not as valuable as the first. A third even less so.

Finding a profitable exchange depends most importantly on how many members are shaping the market. Thus, when the number of agents and items increases, chances for GDAs increase. In the model, GDAs start with an item belonging to a range and aims for an item from the last range. *Social mobility* is the degree to which an individual's social status can change within a society throughout the course of their life through a system of stratification (i.e. levels based on wealth or power). Subsequently, it is also the degree towards where individual's or group's descendants move up and down the class system. In the model, class is related to the range that the item's agent belongs. For example, societies which use slavery are an example of low social mobility because, for the slaved individuals, upward mobility is practically nonexistent. Only rich individuals have opportunities to improve.

We have explored the behaviour of population of selfish agents. The most significant findings are:

- Under some conditions in the market it can be shown with certainty that a GDA reaches the desired item, even when all the agents in the market are selfish.

- As greater numbers of GDAs enter the market, the more difficult it is to reach the desired items – however that this change is non-linear in the growth of the number of GDAs.

- The richer an agent is (i.e. more close to the last range) the more opportunities, the easier it is to reach the highest level.

- BT mechanisms improves the performance when the quantity of GDAs is reduced but with many GDAs BT does not improve the results.

With respect to value–enhance action and devaluation process:

- $GDAs$ that can value–enhance more categories and that make best enhancement (i.e. maximizes the IV) are more likely to get an upper range.

- Obviously, the fewer categories a GDA is related to the quantity of value–enhanced items decrease. Also, as decreases the IV the quantity of jumps decreases.

- In a scenario where a GDA can improve one item enough to be useful for a PA in a range the GDA will trade up. If this GDA is capable of doing this in all the ranges in the path (i.e. from the paperclip to the house) it should get its objective.

- To be able to value–enhance items is more valuable in environments where it is more difficult to exchange items. However, when the quantity of $GDAs$ is off–balance with respect to the PAs, the ability to value–enhance items is not enough to improve the performance in the market.

Kyle's environment differs from our environment in two main points:

- The quantity of agents and items tends to infinity. Also, the market is composed by one GDA and the rest are PA. But this is only one instance of the proportions of agents that a market can have. For example on www.eBay.com there is a red paper–clip on sale for $1 but nobody offers even this $1.

- Some agents accept trades that are not beneficial to them. At least not beneficial with respect to the established/general economical rules (i.e. the agent gives more value than that it receives in exchange). Merely evaluating the value of the item in the exchanges way lead us to a assume that a seemingly altruistic exchange has occurred. However, as we should always bear in mind that the goal of the GDA is a final objective, other factors need to be taken into account when evaluating the exchange. These may include publicity, excitement and so on compensating the seller and turning an altruistic exchange into a beneficial exchange.

7.4 Conclusions and Future Work

The experiment reveals that Kyle's feat is possible but only under a strict a set of environmental conditions. Furthermore, this experiment shows the environments where the above is possible and where it is not.

With respect to the results obtained from the simulator:

- With limited information is not guaranteed that GDA reaches the objective. GDA's knows how far to the MV is but also does not know what is the right sequence of trades nor what are the next items.
- With competition (i.e. more than one GDA) many chains of trades could be cut.
- The quantity and type of agents have a direct impact in the performance.
- When items tends to infinite the probability of passing from g_{worst} to g_{best} is ≈ 1.

The advantage of this environment is that it succeeds because it only relies upon the exchange of reciprocally valued items in the system. This will continue until the goal driven agent reaches its desired items, but during the process everyone else gained too.

The enormous opportunity of peer–to–peer commerce ([36], [32], [124]) is that it is the most extreme form of dynamic pricing, where each party values their currency differently. The dynamics of completely decentralized bilateral exchange are complex systems consisting of larger numbers of agents involved in massively parallel local interactions/decisions. See [88], [181]. As Negroponte predicted in its article Peer–To–Peer Payoff "Swapping is a very attractive form of exchange because each party uses a devalued currency, in some cases one that would otherwise be wasted". See [111], [162], [1]. Likewise, the person with whom you are swapping is giving something of value to you which is less valuable for them. Speculation and arbitrage opportunity is in ordinary usage in the Internet Age and it appears in examples as betting exchange or Massive Multi–player Online Role–Playing Games (MMORPGs). With respect to the value–enhance process when there are few $GDAs$ many paths to the end are open for them. Increasing the possibilities to search a counterpart interests in the item. However, when the quantity of GDA increases they eliminates many paths that allow to improve to the rest of $GDAs$ population.

The economies studied in this case are simple but show interesting dynamics as the result of even simple effects/actions. A value–enhance action allows to agents improve the values of the items. This action increases the opportunities to trade. On the other hand, the devaluation process which decreases the value of the items. This action decreases the opportunities to trade.

- With one GDA using BT, the benefits for that GDA in relation to others not using BT is very big. However, when BT is replicated by a large number of agents the market becomes more competitive and the advantage for individual $GDAs$ is reduced.

- A value–enhance action is necessary to make the item attractive to other agents.

- Agents with value–enhance (VE) action are selfish in terms of the benefit, as the VE action only benefits themselves. The VE action has no knock–on effect for agents not using the VE action.

A feature to emphasize is that in our model no one follows an altruistic behaviour. In the trading process, every agent can improve their initial satisfaction or they prefer not to trade. The GDA has a different perception of value, they only care about MV and reaching the last range. Therefore, the results show that where the quantity of PAs is greater than $GDAs$ it is possible that these $GDAs$ reach the desired item. On the contrary, when the quantity of $GDAs$ is greater in the population, all of them do not reach the desired item.

Future research includes other modelling choices, such as:

- Non–linear value ranges: Instead of ranges with the same quantity of items the market will have ranges with a quantity of items depending on its value. For example, as MV increases, there are less items in a range.

- Opportunistic GDA: The new GDA can predict future price movements for stocks and commodities through observing and analysing past and current market trends (i.e. the economic benefits of speculation).

- Looking up process and cost: To establish some balance or mechanism to obtain the best balance between the cost to discover good trading and the benefit obtained with the trade. The transaction cost of discovery might be very high and this might be the undoing of a project like One Red Paperclip. How does Mr Paperclip know that exchanging P for Q gets him closer to Z? Do the self-organizing benefits of a free market really come into play when there is one person essentially trying to coordinate? Finding the individual exchanges that would lead to a particular goal sounds like a job for the market as a whole, not one individual.

7.5 Summary

In summary this chapter shows:

- **Environments' parameters:** Quantity of items, agents and ranges, distribution of PV and MV.
- **Distribution of $GDAs$:** With many $GDAs$ the opportunities to get a good item decreases.
- **Backtracking:** Backtracking improves the results with few $GDAs$ but when the ratio of GDA:PAs is unbalanced, the backtracking also suffers from saturated trading paths.
- **Value–enhance action and devaluation process:** These two parameters turn the model into a more realistic model. Showing the dynamics when agents can value–enhance items and when the past of time/use devaluates the items.

Chapter 8

Distributed Barter–Based Directory Services

This chapter is motivated by the need for new solutions to the management of directory services and in particular, the need to provide more *autonomy* in such service [145]. In order to achieve this autonomy whilst maintaining a fully functioning directory, a bartering strategy is used. The chapter describes the model and experiments carried out in Distributed Barter–Based Directory Services (*DBBDS*). The major challenge involved is to build a workable system which not only responds to queries from users but A) ensures that directory items are never lost in the system and B) optimizes query response time with respect to different patterns of query arrival.

The primary function of *directory services* is to repeatedly allocate a set of entries in accordance with clients demands at successive times. The basic model behind these services involves partial customer preferences over entries, and the directory service aims to satisfy these preferences as quickly as possible.

Distributed sets of networked computing resources require *directory services* that store information about network resources. With the adoption of decentralization approaches in the distribution of administrative control, even though a common policy is adopted, no one individual entity is in control of the whole information. In such scenarios, all individuals work cooperatively following the same aim to respond to the queries delivered by the clients.

An autonomous and distributed barter–based implementation of the directory services combines [93] simplicity and distributed nature of barter. An additional benefit of bartering content is that its nature forces the nodes that store information to maintain entries in the system, making entries highly available and less likely to be lost due to failures. Furthermore, in a com-

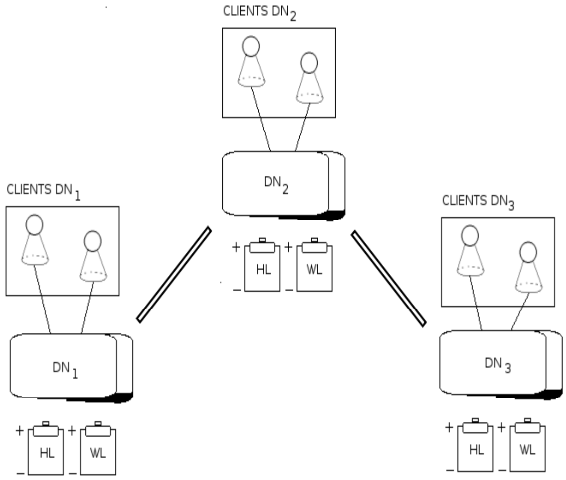


Figure 8.1: Clients request for directory items. The distributed directory services manages these queries.

petitive environment such a marketplace, a peer may not forward search requests nor can it maliciously not provide the content that it is responsible for [195]. Bartering has implicit strategies based on reciprocity and feedback which encourage cooperation between participants. These advantages over the traditional server–based implementation promote this work.

The aim is to build a *distributed directory service* that:

- Manages the queries made by the clients using a team of cooperating and competing directory services.
- Ensures that directory items are never lost in the system.
- Optimizes query response time with respect to different patterns of query arrival (see Figure 8.1).

For Zheng [197] “A major drawback of existing large scale content distribution systems is the directory services, which generally consists of an index server and a tracker server. The index server (e.g. a web server) hosting all the metadata of shared content. A user will have to contact the index server to search for specific content and retrieve the metadata of the interested file. After that the user launches the client download software to connect to a tracker server in order to get a list of peers who are downloading the same file. In effect, such a directory services does not scale well as it cannot accommodate a large number of requests when the population of the system increases rapidly.”

As the world grows more connected it becomes more complicated to find out a desired item. In this complex world, we need ways of defining and identifying resources and services. The simplest way to do this is with registries applications. An Internet back bone application has been developed using a barter–based approach in order to contact easily a specific content. An autonomic and distributed barter–based implementation of the directory services combines [93] simplicity and distributed nature for bartering with scalability, robustness, distribution of control from the peer–to–peer approach. An additional benefit of bartering content is its nature that forces that nodes to maintain entries in the system, making it more available and less likely to be lost due to failures. These advantages over the traditional server–based implementation promote this work. The innovation of this work is to manage users' access to the resources applying *barter mechanism*.

The primary function of distributed directory services is to repeatedly allocate a set of entries in accordance with clients demand at successive time instances. The basic model behind these markets involves (partial) customer preferences over entries, and the directory services aims to satisfy these preferences within the constraints of available own inventory (i.e. the entries in the directory).[2]

The advent of powerful computing facilities in the participants has enabled two important paradigm shifts over the last decade. The first shift is the move away from categorizing entities according to the traditional client-server model, and the second is the progressive adoption of decentralized overlay systems. Both paradigm shifts dramatically changes the way in which communication systems are designed and build; and both are pertinent to the realization of truly autonomic communication systems. The adoption of further decentralization [163], which in part is expedited by the desire to utilize the improved capabilities of end hosts, allows the distribution of functionalities across a subset or the whole of the participating end hosts, providing the advantage of robustness by removing single-point failures in the system. Furthermore, the resources, and thus the cost, required to provide the functionality can be distributed to all participants. Finally, decentralization results in the distribution of administrative control so even though a common policy is adopted, any individual participant is in control of the whole system.[50]

Therefore, the major challenge in the implementation of directory decentralized system is to build a system that without a central coordination unit achieve that the system works correctly in an environment where:

- Participants can come and go.
- No participant hierarchy.

- No naming structure.
- Data is of interest, not the participants.

Two approaches can be envisaged:

- **Directory–based architecture:** In this architecture some participants with better computation and memory resources are selected as Directory Agents (*DAs*) that keep a repository of all the service information in the network in a directory. These *DAs* advertise themselves to other participants. Service provider participants register with these *DAs*. Clients contact these DAs to get the location of service providers. Examples include Jini[1], Universal Description Discovery and Integration (UDDI)[2] and Salutation. This approach is suitable for infrastructure–based networks or when changing topology is not a matter.
- **Directory–less architecture:** In this architecture there is no service coordinator. Clients contact service providers directly by flooding the service query. This result in a high overhead produced due to flooding. Examples of this architecture include Service Location Protocol (SLP)[3] and Universal Plug and Play (UPnP)[4].

Other relevant issues include:

- **Resource Discovery:**
  - **Centralized matchmaking:** The simplest architecture for forming exchange groups is for all participants to send a list of items they possess and a list of items they are interested in to a centralized matchmaker service. Given such global information, to look for a global optimal allocation is possible. Centralized matchmaking has the advantage of complete information, but it has the obvious disadvantage of being a scalability bottleneck and a single point of failure in the system. And in many cases it is not an available solution.
  - **Partitioned matchmaking:** Instead of having a single centralized matchmaker, an alternative is to have many dedicated matchmakers, and to divide the population amongst these matchmakers.

[1]Jini in http://www.jini.org
[2]UDDI in http://www.uddi.org
[3]SLP in http://www.ietf.org/rfc/rfc2608.txt
[4]UPnP in http://www.upnp.org

This suggests that a partitioning strategy would work well, since each partition is effectively a separate, small population of users.

  - **Decentralized matchmaking [39]:** Instead of having dedicated, partitioned matchmakers, fully distributed equivalents could exist. One possibility is to have participants volunteer to be matchmakers, in a manner similar to how some participants in existing P2P item-sharing systems promote themselves to be super–nodes, indexing content to satisfy queries. Another possibility would have participants organizing into an overlay, and to broadcasting their owns-item/have–list and wants-item/want–list sets across the overlay; participants would listen to broadcasts as well as sending them, searching for possible circles and proposing them to each other as they form. A final possibility would be to use distributed hash tables (DHTs) (see [20], [121]) to store the owns-item and wants-item sets of each user in a distributed, inverted index: given the name of an item, the DHT would return the set of users that want the item. Given the name of a user, the DHT would return the set of items that user owns.

- **With respect to the quantity of entries per participants:** Imagine a configuration where every node maintains the complete entries. In terms of query routing that would be a perfect situation, because every query could be routed directly to the correct node(s) but updates would be extremely expensive and indices would be very large.

- **Selfish agents:** Stirrat and Henkel (1997) argue that giving pure gifts may also be harmful to the relationship between givers and receivers, if reciprocity is wanted by the receiver but, for whatever reason, not feasible. In this case, individuals who do not have the resources or capabilities to give something back are left in a position of indebtedness and powerlessness. "Pure gifts are good for the giver but, symbolically at least, bad for the receiver". On the other hand, if not meant as a pure gift but in expectation of something in return, givers may feel exploited over time and the problem of free-riding occurs. The community then, suffers from the *social dilemma* which occurs when contributors, then, cease from giving, although everybody would be better off if people contribute. See [104], [132], [172]. Humans come equipped with *selfish genes* [53]. This result from the Darwinian selection process that guides the evolution of life. In an environment of limited resources, the particular gene tends to become extinct and so does the strategy that this gene codes for. The selfishness and rationality of individuals has long been a standard assumption in the social sciences and in Game Theory [134]. And this is the approach that we will follow in our model.

- **Assuring replicas/availability:** Participants may join and leave the system at any time.[45]

- **Performance:** The query distribution is a relevant element that it has a great effect in the performance of a directory system based on bartering.

- **Distributed authorization/manage/control:** In DNS and X.500 the set of entries are partitioned in boundaries are often indicate organizational boundaries.[73]

8.1 The DBBDS Model

Distributed Barter–Based Directory Services (*DBBDS*) is an approach based on a set of interconnected peers called *Directory Nodes* (*DN*). Each *DN* only has partial knowledge of the network, no one has all the information/entries. A *DN* in *DBBDS* is part of a directory services team (see Figure 8.5). This team manages the queries requested by the clients of the directory service. This team is a community of cooperating and competing components. The obligations that any *DN* has as a member of the *DBBDS* are:

- To keep a set of entries.

- To respond as fast as possible to the clients' queries.

Each *DN* in the directory services has the following features:

- Each *DN* is autonomous and self–interested.

- Links between *DN* are used to find a *DN* which can resolve a query.

- Each *DN* takes local decisions. The information comes from requests from own clients and requests provided by neighbours.

- Each *DN* keeps a list of entries and it is responsible for the storage of keys (i.e. similar to Chord). The only way to change an entry is by means of a bartering deal.

- Each *DN* has limited resources such as storage capacity, information.

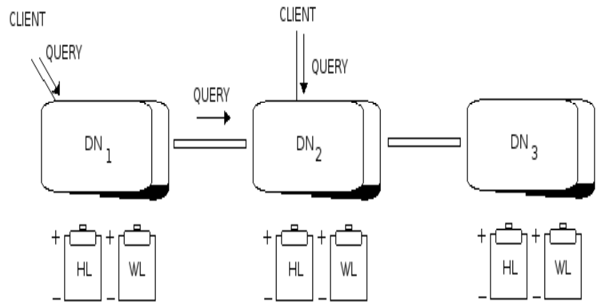


Figure 8.2: The DNs are linked shaping a directory services network. Each DN has a set of clients associated.

The DNs have limited resources and are required to make a commitment to keep local entries as members of the *DBBDS*. Perhaps these entries are not useful for them at the current moment but these entries could be useful in the future, or necessary for other DNs. Under no circumstances should the DN removes an entry. As distributed cooperative directory services, the team of DNs should respond to any entry that can be requested by any client in the system at any time. The DNs keep the set of entries. If the storage capacity has reached the limit of entries that it can store, no more entries can be kept. The only way to change entries it is establishing an exchange with a neighbour (i.e. barter an entry for another entry).

The set of DNs are a collaborative network such as Internet e–mail. In e–mail there will only rarely be a direct connection between your network and the recipient's network, mail will make a number of stops at intermediate networks along the way. At each stop, another e-mail system temporarily stores the message while it figures out the best way to relay the message toward its ultimate destination. In *DBBDS* the DN aims is to respond as rapidly as possible to the clients' queries. For this reason, each DN desires to entries most requested by its own clients as near as possible at hand and at the same time not to be responsible of entries that are not interesting for its clients.

When a query can be directly responded to, the time to respond is equal to one tick. When this is not possible, the client's query is forwarded to the DNs neighbours increasing the response time. The further away the requested entry is, the more time it takes. Queries that cannot be answered by the DN are re–sent to the DN neighbours. Once the client sends a query to the DN which it is related to, these DNs search in its have–list. If the requested entry is not in the have–list, the query is re–sent to the DNs

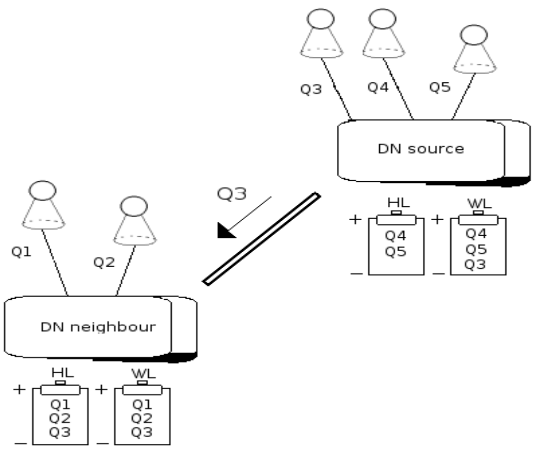


Figure 8.3: Scheme of queries in DBBDS.

neighbours until some DN has the entry or the life–time of the query expires (i.e. following a flooding queries schema – the query is propagated to all neighbours within a certain radius). Figure 8.3 shows two DNs where the clients send queries to the DNs which they are associate to. The clients of DN_{source} are requesting $Q3$, $Q4$ and $Q5$. It makes that these entries have more value for DN_{source}. The entries $Q4$ and $Q5$ can be respond by the DN_{source} but, it is not so for $Q3$. This should be requested by DN_{source} at its neighbours.

The information useful, and available to the DNs are:

- Have–list (HL): The list of entries that the DN has.
- Want–list (WL): The list of entries that the local and foreign clients want.
  - Local clients queries: Queries from clients directly connected to DNs.
  - Foreign clients queries: Queries come from clients of others DNs.

Each one of these lists is composed of two components:

- Node directory entry: Contains the address for each remote workstation.
- Request rate (RR): This component defines the order in the list.

The experimentals have the following parameters: **Time window (TW):** The time window is employed to balance new information against past experience. A request is limited to a specified time window beginning with time t_1, and extending up to time t_2 (i.e. window time interval $[t_1, t_2]$). Following this approach, the oldest requests will be removed from the WL replaced by new requests.

Query distribution (QD): The query distributions that the population follows:

- An uniform query distribution: All the entries have equal probability for getting requested.
- A Zipf query distribution: In Zipf–like distribution, the number of queries to the i'th most popular object is proportional to $i^{-\alpha}$, where α is the parameter of the distribution. The query distribution has a heavier tail for smaller values of the parameter α. See [26], [148].

A Zipf distribution with parameter 0 corresponds to a uniform distribution and with a value α equals to the unity follows a Zipf distribution.

Content Distribution (CD): The volume and type of content each DN carries.

Request Generation Rate (RGR): Clients in a *DBBDS* issue queries to search for entries that match their interests. A client without an entity will generate a search request for the entity at certain rate depending on the preference for the entity. Each client i is assigned a query generation rate q_i, which is the number of queries that client i generates per unit time.[138]

Pressure of foreign queries (PFQ): This parameter allows the importance/significance of the external queries with respect to the local queries to be set up.

- $\lambda_I = 0$ the queries from foreign clients/DNs have the same importance than the queries from local clients.
- $\lambda_I = 1$ the queries from foreign clients/DNs have less importance than the queries from local clients.

Figure shows an example related to the lambda or pressure parameter. In this case, the client$_A$ of DN_A sends the query Q_A. This query is resend to DN_B and DN_C, when lambda is equal to zero the entry is the most relevance for the three agents. However, when lambda is one, the rest of agents prefer queries from own clients.

Topology (T): The topology of the network establishes the links from peers to a number of peers.

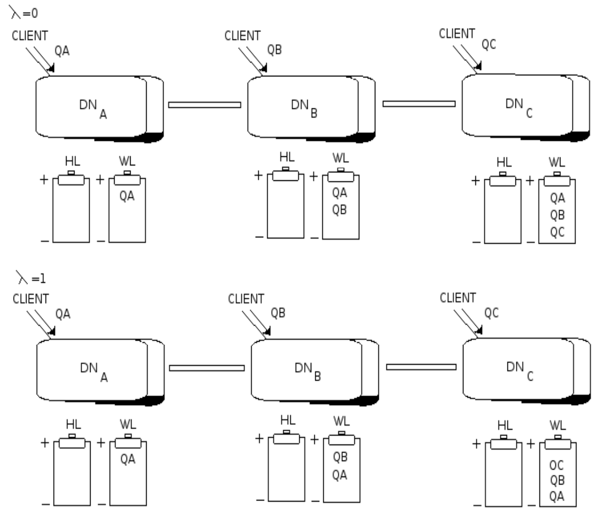


Figure 8.4: Examples of relevance in the entries when lambda is equal to zero and one.

Time to Live (**TTL**)**:** Before re–sending a query the TTL field is increased if the new value is higher than a certain threshold the query is not resent. Otherwise, the query is resend to the DNs neighbours.

Updating WL and HL: The process to update the order in WL and HL follows the algorithms proposed in algorithm 6. In the algorithm Q_L is a query from a local client. For foreign queries the algorithm is the same as for the local query except for the first conditional that it does not appear and changing Q_L by Q_F that is the foreign query. The local queries update the utility/satisfaction in the WL and HL of the entry associated to the query. For foreign queries only the WL is updated because the HL is restricted for local queries.

Algorithm 6 Local Query

if $Q_L \in HL$ **then**
  to update the rate request of Q_L in HL
  $HL \Leftarrow Q_L$
end if
if $Q_L \in WL$ **then**
  to update the rate request of Q_L in WL
end if
$WL \Leftarrow Q_L$

8.2 Implementation Overview

In order to analyse our model, we conducted simulation experiments to judge what is the performance of query response time and how content is distributed and re-allocated in the system. Simulations were performed to assess the effectiveness of the service directory infrastructure. It is assumed that the agents themselves are reasonably long–lived and static.

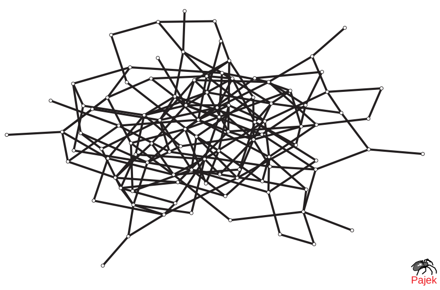
A simulation starts by placing the m distinct entries randomly into the DNs network. Then the clients start to generate queries according to a Uniform/Zipf-like process with average generating rate at a queries per tick to its DNs. These queries are analysed by the DNs. In case that the query is one of the entries in the HL, the query is responded to and the entry updated (i.e. increasing its value). If DN does not have the entry, the DN resend the query to its neighbours and it updates the WL. With the information provide from HL and WL, DNs offer to its neighbours the entries that they want and it does not want. The only way to get valuables entries is offering valuables entries to the neighbours. Therefore, the process to update the HL and WL allows to DNs distinguish between devaluated and not devaluated entries in order to establish beneficial exchanges. The simulation finishes when all the clients queries are processed or time finish is reached.

8.3 Experiments

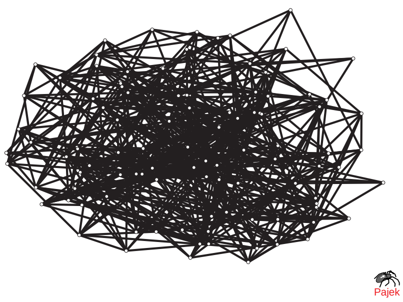
The paper provides experimental results for the following parameters:

- TW: 8.
- QD: Random distribution, perfect and non–perfect Zipf distribution.
- CD: 500 entries distributed in 5 entries per DN.
- RGR: Each DN only has an unique client. And each client only wants an entry per unit of time following the QD.
- PFQ: lambda is equal to zero when the DN gives the same priority to local and foreign queries and lambda is equal to one otherwise.
- T: 100 DNs following a Erdos–Renyi structure[5] (see Figure 8.5). The number of unreachable pairs is equal to 0.

[5]Erdos structure has a densely concreted core along with loosely coupled radial branches reaching out from the core.



(a) Network 1.



(b) Network 2.

Figure 8.5: Topologies used in the experiments.

- Network 1: The average distance between reachable pairs is 3.66 and the greatest distance between vertices (i.e. diameter) equals 8.
- Network 2: The average distance between reachable pairs is 2.44 and the diameter equals 4.

- TTL: Time to live, with values from 0 to 4.

Performance parameters studied:

- Response Time: The response time is defined as the number of hops between the source and the destination.
- Percentage/Rate Success Response: The percentage of request that are responded.
- Quantity of exchanges: The quantity of exchanges (i.e. one entry by other entry) that are made in the system.

The first two parameters are related to service quality the third is related to the performance of the exchange strategy.

8.3.1 Random and perfect Zipf query distributions

This section contains a comparison of the worst and the best scenario for the exchange–based system. If the preferences of the clients follow a random distribution, the DN cannot put a stable order to these preferences. The bartering mechanism is a very attractive form of exchange but each decision–maker needs to know the devalued and value–increased entry. Also, this knowledge should be stable enough to be applied to the exchange process. On the other hand, in a perfect Zipf distribution, with the passing of time, DN knows the needs of their clients are, keeping the most valuable entries and using the rest to barter. Also, in a perfect distribution there is no competition amongst DNs.

Figure 8.6 shows the performance in network 1 of the system when the clients follow a random query distribution. The exchange policy, in this case, neither when $\lambda_I = 0$ nor with $\lambda_I = 1$ have positive results. Also, in both cases the quantity of exchanges is significant. On the contrary, in Figure 8.7 when the distribution follows a Zipf shape. Using an exchange policy the performance is improved. Concretely, the exchange policy reduces the query response time in a 41 % when $TTL = 4$ and 3. At the same time, the query success rate improves by 40 % when TTL =2. For lower $TTLs$ values the exchange policy does not improve significantly due to few changes being possible. If the quantity of neighbours DNs that knows the needs of a DN the opportunities are reduced. Comparing the pressure of foreign queries, with $\lambda_I = 1$ the quantity exchange decreases due to the DNs giving more priority to the queries from their own clients than queries for foreign clients, but the performance is better.

When using the exchange–mechanism the improvement for clients is also significant compared to a system where no exchange mechanisms are introduced. This observation suggests that DNs have a good incentive to deploy the proposed exchange mechanism.

Comparing the values in Figures 8.6 and 8.7 the first scenario corresponds to the worst case scenario and the second to the best case for the barter–based approach. When the clients follow a query random distribution, both parameters response time and percentage success response are similar. However, when the clients follow a perfect Zipf query distribution, an improvement in both the response time and in the percentage of successful responses can be seen. Also, the quantity of exchanges reveals that with a random query distribution the quantity of exchanges is much greater than with a perfect

Zipf query distribution. The reason for this poor performance and the large number of exchanges is due to in a random query distribution the DNs have an unstable list of what the clients wants. This fact implies that they are trying to get many different entries and usually they have not these requested entries. On the other hand, when the clients follow a perfect Zipf query distribution, the DNs keep a stable list of entries that the clients want and no other DN wants these requested entries. These two factors facilitate the improvement of the performance.

With respect to the topology Figures 8.7 and 8.8 are simulations where the only modified parameter is the topology used. In Figure 8.7 with network 1 and in Figure 8.8 working with network 2. Being the average distance amongst reachable pairs equal to 3.66 in network 1 and 2.44 for network 2, it reveals the relevance of topology in the percentage of success response parameter. When TTL is greater than 3 in network 1 and TTL greater than 4 in network 2 when the percentage of success with or without exchange policy are similar. However, under these thresholds the results show that when working with exchange policy, the percentage of success is always better. Without the exchange policy and a limited TTL many queries are unreachable by the clients.

8.3.2 Non–perfect Zipf distributions

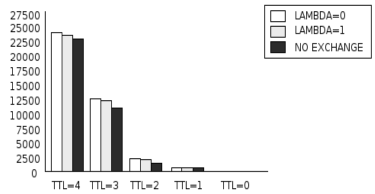
In the previous section two extreme scenarios were shown. Now, the performance obtained in middle scenarios is explained. From perfect to fully non–perfect Zipf distribution in network 1:

- 0 %: The queries follow a perfect Zipf query distribution. The clients related to each DN only send queries from the range that belongs to the DN. This scenario is exactly the same when clients follow a Zipf perfect query distribution.

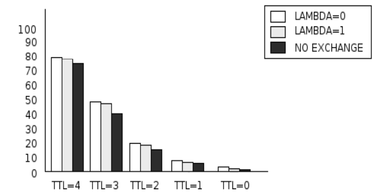
- 25 %: 75 % of the queries follow a perfect Zipf query distribution but 25 % of the queries follow a Zipf global query distribution. This means that the clients, in a percentage of 25 % send queries to the most popular entries in the whole directory.

- 50 %: 50 % of the queries follow a perfect Zipf query distribution but 50 % of the queries follow a Zipf global query distribution.

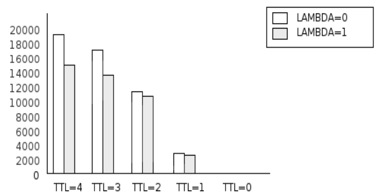
- 75 %: 25 % of the queries follow a perfect Zipf query distribution but 75 % of the queries follow a Zipf global query distribution.



(a) Response Time.

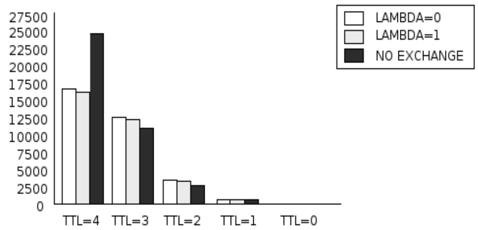


(b) Percentage Success Response.

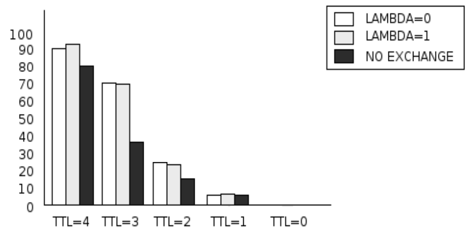


(c) Quantity of Exchanges.

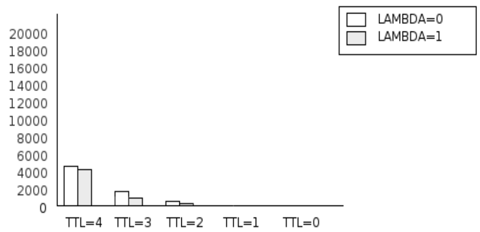
Figure 8.6: Query random distribution in network 1.



(a) Response Time.

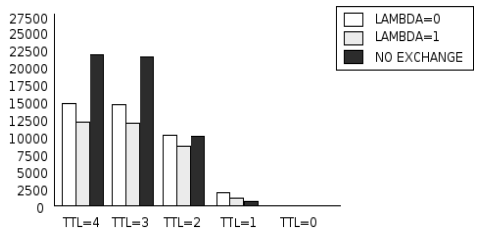


(b) Percentage Success Response.

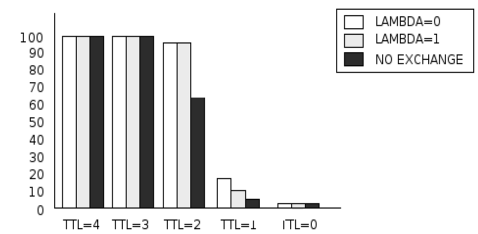


(c) Quantity of Exchanges.

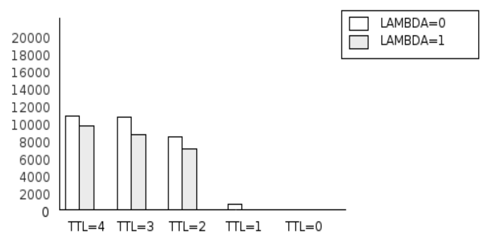
Figure 8.7: Query Zipf local distribution in network 1.



(a) Response Time.



(b) Percentage Success Response.



(c) Quantity of Exchanges.

Figure 8.8: Query Zipf local distribution in network 2.

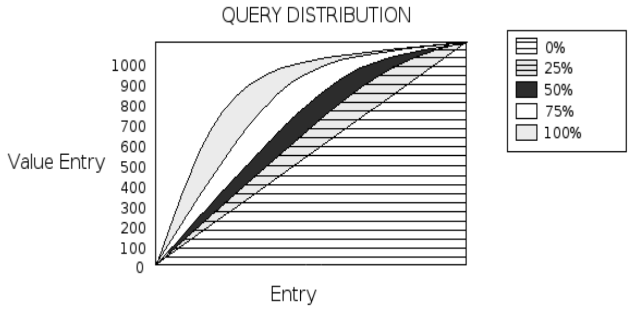


Figure 8.9: From perfect to fully non–perfect Zipf distribution.

- 100 %: the queries follow a Zipf–distribution. This means that the clients always want the most popular entries the directory.

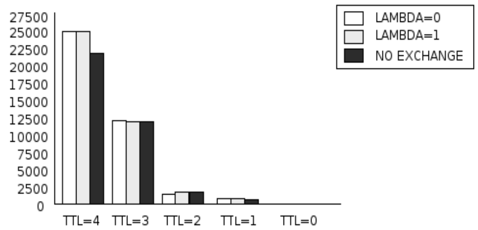
Figure 8.9 shows the non–perfect Zipf query distributions from 0 % to 100 %.

Figures 8.10, 8.11, 8.12 and 8.13 show the performance parameters in non–perfect Zipf query distributions from 100 % to 25 % in network 1. As more clients request the most popular entries (i.e. to turn a perfect into a non–perfect distribution) the response time and the quantity of exchanges increase, and the rate of success decreases, as more clients wants the most popular entries of the directory. When all the clients are requesting the same range of popular entries (i.e. 100 %) the response time is increased due to DNs with popular entries not liking exchange these entries. Unpopular entries are requested from time to time, but in any case these requests could imply many exchanges.

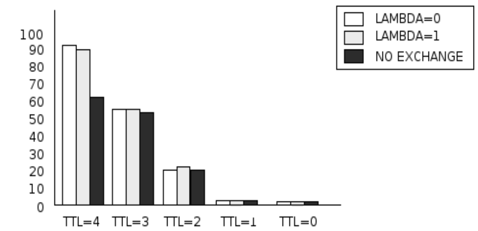
Global Zipf query adds competition amongst DNs with respect to the local Zipf query distribution. This competition has a dual consequence: both the quantity of exchanges and the response time are increased.

8.3.3 Flash crowds

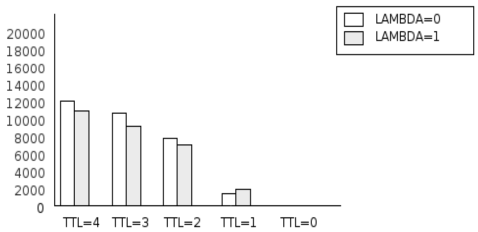
This section shows the behaviour of the policy exchange–based mechanism which is constantly changing. A flash crowd is the attention of a large number of people, and gets an unexpected and overloading surge of traffic. In this



(a) Response Time.

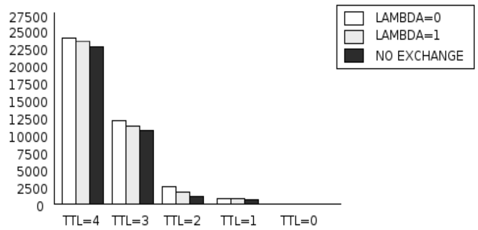


(b) Percentage Success Response.

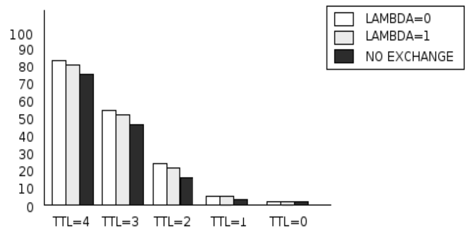


(c) Quantity of Exchanges.

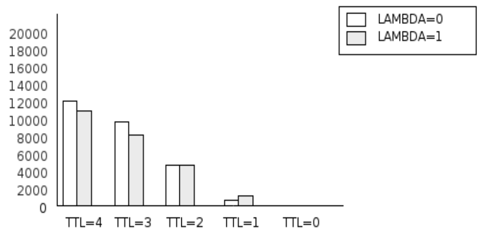
Figure 8.10: Non–perfect Zipf distribution 100 %.



(a) Response Time.

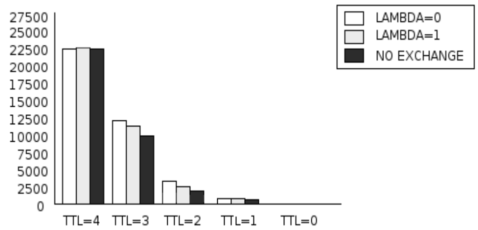


(b) Percentage Success Response.

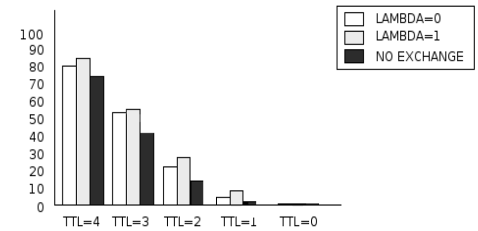


(c) Quantity of Exchanges.

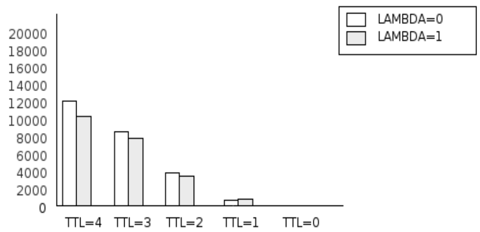
Figure 8.11: Non–perfect Zipf distribution 75 %.



(a) Response Time.

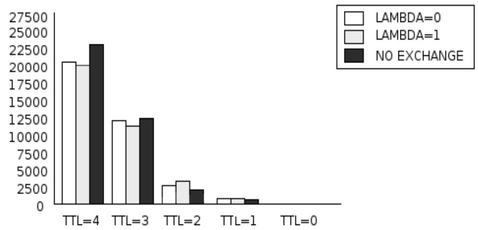


(b) Percentage Success Response.

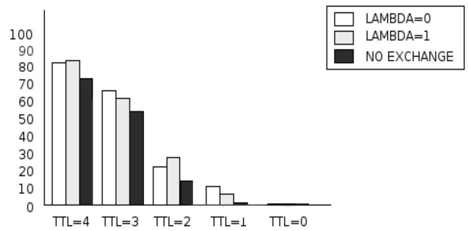


(c) Quantity of Exchanges.

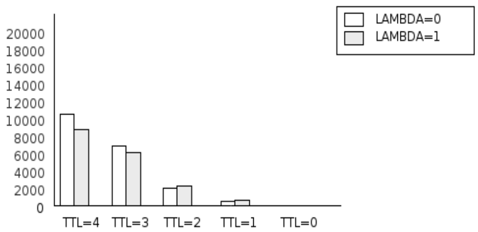
Figure 8.12: Non–perfect Zipf distribution 50 %.



(a) Response Time.



(b) Percentage Success Response.



(c) Quantity of Exchanges.

Figure 8.13: Non–perfect Zipf distribution 25 %.

case the experiments are showing the effect caused by many participants repeatedly requesting entries. This is important as it is need to know if the performance has some variation with the passing of time. The clients have preferences that are not changed during the rest of the simulation. The expectation is that, due to clients always wanting the same entries, performance improves during the simulation. The experiments range from perfect to fully non–perfect Zipf distribution. For each scenario, the three parameters studied are: response time, percentage of success response and quantity of exchanges.

The next three figures are related to flash crowds process:

- Figure 8.14 shows the results when lambda equals zero working with network 1 and following a Zipf local query distribution. In this case, this is a sudden change in the query distribution. In the experiments, during 100 steps, the clients of the DN send queries into a similar range. Once spend the time the clients changes the range of queries.

- Figure 8.15 shows the results when lambda equals zero working with network 1 and following a random query distribution. In this case, only the local query distribution is changed. This means that global queries are stable. Therefore, when the global queries are the 100 % of the queries, query distribution is the same in the three simulations.

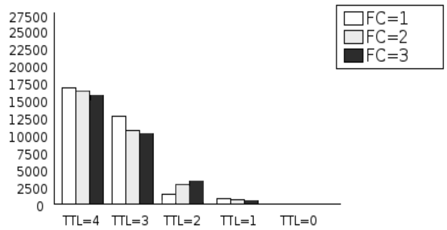
- Finally, Figure 8.16 shows the results with lambda equals zero working with network 1 and following a Zipf global query distribution with 100 %. In this case, the query distribution is the same in the three simulations.

Figure 8.14 shows the increase in the quantity of exchanges due to during the exchange process the DNs are getting the entries that they want. Once changed the range in the query distribution the entries are fast to each DN. On the other hand, in Figure 8.15 and Figure 8.16 the distributions are fixed and at any flash crowd the quantity of exchanges decreases at any simulation.

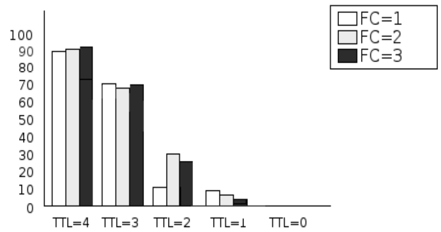
8.4 Conclusions and Future Work

The following properties were obtained from the previous results:

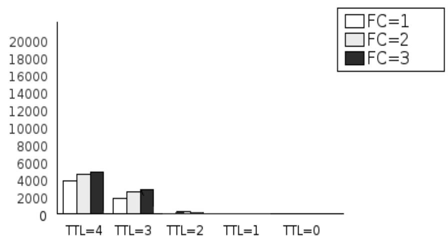
- The topology affects the information that DNs should evaluate in the exchange process.



(a) Response Time.

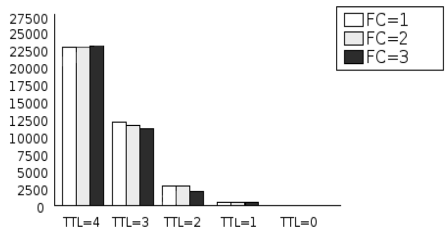


(b) Percentage Success Response.

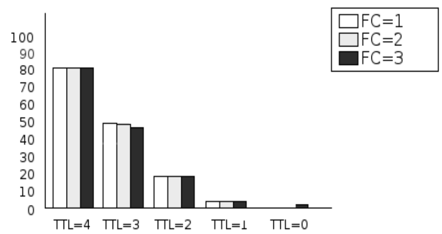


(c) Quantity of Exchanges.

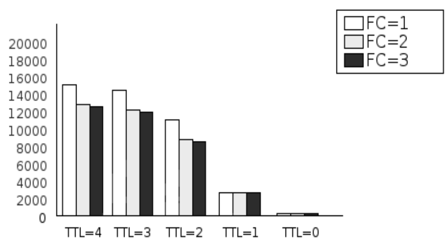
Figure 8.14: Flash crowds with Zipf local query distribution.



(a) Response Time.

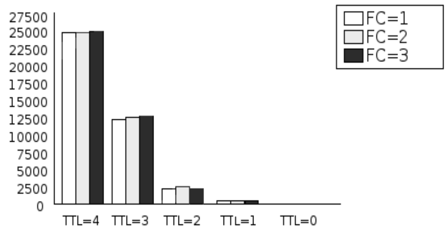


(b) Percentage Success Response.

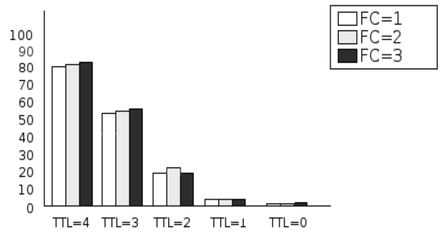


(c) Quantity of Exchanges.

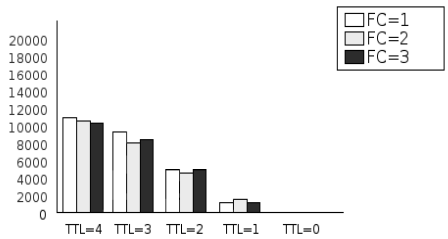
Figure 8.15: Flash crowds with random query distribution 100 %.



(a) Response Time.



(b) Percentage Success Response.



(c) Quantity of Exchanges.

Figure 8.16: Flash crowds with Zipf global query distribution 100 %.

- The TTL parameter limits the propagation of the query. In our case however, it also limits the propagation of the updating of the WL and the opportunities to establish exchanges.

- Increasing the TW, the WL holds the clients' requests longer. This information increases the opportunities to make exchanges.

- Due to all the clients of a same DN following the same Zipf–local query distribution the pressure on the DNs (i.e. in the DNs' WL) increases, thus increasing the response queries and diminishing the quantity of messages. Turning perfect query distribution to non perfect one that will have a negative effect on the performance.

Barter–based systems bring several advantages. Firstly, they preserve the autonomy of individual participants. Each participant makes local decisions about whom to trade with, how many resources to contribute to the community, how many trades to try to make, and so on. Secondly, the symmetric nature of trading ensures fairness and discourages free–loading (i.e. bartering is an incentive scheme by nature). In order to acquire resources from the community, each participant must contribute its own resources in trade. Moreover, participants that contribute more resources receive more benefit in return, because they can make more trades. Thirdly, the system is robust in the face of failure. Robust in the sense that the exchanges are one–to–one and this not has the weakness of economic environments.

The advent of powerful computing facilities in the participants has enabled two important paradigm shifts over the last decade. The first shift is to move away from categorizing entities according to the traditional client-server model, and the second is the progressive adoption of decentralized overlay systems. Both paradigm shifts dramatically change the way in which communication systems are designed and built; and both are pertinent to the realization of truly autonomic communication systems. The adoption of further decentralization, which in part is expedited by the desire to utilize the improved capabilities of end hosts, allows the distribution of functionalities across a subset or the whole of the participating end hosts, providing the advantage of robustness by removing single-point failures in the system. Furthermore, the resources, and thus the cost, required to provide the functionality can be distributed to all participants. Finally, decentralization results in the distribution of administrative control so even though a common policy is adopted, no one individual participant is in control of the whole system. Therefore, the major challenge in the implementation of a directory decentralized system is to build a system that works correctly without the need for a central coordination unit.

The distribution of a set of entries amongst a set of distributed and autonomous agents, with varying preferences, is a complex combinatorial problem. Bartering can be used as a form to resolve this problem. In barter exchange each party uses a devaluated currency, in some cases one that would otherwise be wasted. The unused entries in your basement can be converted into something you need or want. Likewise, the party with whom you are swapping is giving something that has a greater value to you than it has for them.

Future research includes the study of interest based communities, users that in one cluster share a subset of common entries and are likely to be of interest to other entries popular in the cluster. The transitivity property may be used for enabling private information between users, in order to suggest entries that are potentially of interest for members of the same cluster [117]. Other aspect to study is the tolerance of faults.[103]

8.5 Summary

The aim of the modelled application is to demonstrate that bartering could be used in a real environments paradigm. Taking advantage of the features that characterize Peer–to–Peer applications such as scalability, robustness, and flexibility. And at the same time the market model incentives of the participants publishing names to rely on other participants servers to respond to those names.

In our proposal the system works by following a similar idea but applying a bartering mechanism ([1], [111]). The providers of entries want to have or to have near the content most requested by its clients, it is achieved by exchanging entries with neighbours that follow the same strategy. Therefore, the provider's aim is to respond to client queries. Each self–interested provider/trader starts with some given initial bundle of entries. A new set of required entries, is build up from the clients queries. The providers discuss the proposal distribution among themselves taking the best choice for its clients (i.e. trying to get the most requested entries by its clients). If a provider/buyer decides that it can do better on its own, with its given initial entries, it makes a proposal of exchange that the other provider/seller should evaluate and this proposal only will be accepted if it is beneficial. When both parties accept the exchange entries are transfer among them.[102]

In summary, the oldest method of trade is making up a distributed directory services system. A directory service is simply the software system that stores, organizes and provides access to information in a directory and one of the most important/necessary services in Internet.

PART 3: Contributions and Conclusions

Chapter 9

Contributions and Conclusions

The purpose of this thesis has been to investigate resource allocation using bartering mechanisms, with particular emphasis on applications in large–scale distributed systems without the presence of altruistic participants in the environment. In addition to the individual summaries that are included at the end of each chapter, here we provide an overview of the content of this thesis as a whole.

Throughout the research presented in this thesis we have contributed evidence that supports the leitmotif that best summaries our work: investigating interactions amongst selfish, rational, and autonomous agents with incomplete information, each seeking to maximise its expected utility by means of bartering. We have concentrated on three scenarios: one theoretical, an use case, and finally a realistic application. All of these scenarios are used in order to evaluate bartering in electronic environments. Each scenario starts from a common origin, but each of them has its own unique features.

9.1 Contributions

Let us briefly summarising the contributions of this thesis in relation to its goals:

General Framework:

- A representation of the functioning of a bartering system. The design and development of a general framework applied to three specific scenarios. Each one of these help us to show that bartering is more in use than ever:
  - Development of a bartering network in order to review the efficiency of barter.

  - Development a simple agent population model based on active and passive agents with ranges of personal value without altruism.
  - Design, implementation and evaluation of a distributed directory services based on a bartering mechanism.

- A general framework for bartering mechanism which is simple enough to be applicable in a broad range of scenarios. Revealing the main features related to markets that follow bartering mechanism. To this end, we proposed a framework that can be broken down into three principal components; the model description, the environment and the agent–based simulator. These three components can be extended easily.

- A description of the environment. Focusing on relevant features such as the value of the information, query distribution, topology and the behaviour of the participants. These features appear in different ways in the three technical chapters such as Bartering Networks, Trading Paperclips, Distributed Barter–Based Directory Services.

Bartering Networks:

- Definition of bartering algorithms such as 2–way, 3–way and 3–way recursive. Compare the performance of these algorithms with respect to the optimal performance that it could be obtained by algorithms such as Hungarian method, algorithm of J. Edmonds or integer programming problem.

- Reviewing the conditions (i.e. time and content) of markets.

- Defining and analysing the propagation of preferences algorithm.

- Showing the progression of level of satisfaction with respect to propagation of information and topology

Trading Paperclips:

- Showing that with competition (i.e. multiple active agents), active agents can no longer always achieve their goals.

- Showing the behaviour of mixing strategies (i.e. devaluation and value–enhance action).

Distributed Barter–Based Directory Services:

- Showing the relevance of the topology in the directory services.

- Showing the performance of the service varying the query distribution from perfect Zipf query distribution to non–perfect Zipf query distribution.

The research presented in this thesis is supported by the following publications:

1. Studying viable free markets in Peer–to–Peer file exchange applications without Altruistic Agents (AP2PC 2006 and Technical Report LSI–06–12–R)

   This paper explores the use of simple market mechanisms for P2P file sharing which function without the need for altruistic users considering the conditions under which such markets may be viable.

2. Self–Organisation of content in file exchange markets with self–interested agents (SOAS 2006)

   This paper studies how self–organisation emerges in terms of content distribution. Also, we compare in different scenarios the allocation with respect to the optimal one.

3. Self–Organisation Amongst Non–Altruistic Agents for Distribution of Goods: Comparing Bartering and Currency Based exchange (EUMAS 2006)

   In this paper a number of economically inspired approaches which allow the redistribution of goods amongst agents using self organisation and do not require complete global information or centralised processing are compared.

4. The emergence of order in goods distribution using information and competition (SOAS 2007)

   This paper is concerned with the feasibility of achieving a competitive allocation of items in a decentralised context. The paper reviews the three challenges that affect the optimal allocation such as detection of needs, network structure and individual interest.

5. The impact of the topology on trade in bartering networks– devised and assessed network information propagation mechanisms (CEEMAS 2007 and Technical Report LSI–07–21–R)

   In this paper network information propagation mechanisms are devising and assessing.

Chapter	Related Papers
Bartering Networks	1, 2, 3, 4, 5
Trading Paperclips	6, 7
DBBDS	8

Table 9.1: Relationship between thesis chapters and publications.

6. An Analysis of Paperclip Arbitrage (Technical Report LSI–07-39–R)

   This paper shows the basis of the Trading Paperclips scenario. Showing results related to single and multiple *GDA* and the first results about the backtracking mechanisms.

7. Trading Paper Clips – An Analysis of “Trading Up” in Artificial Societies without Altruists (CCIA 2008)

   This paper is an extension of the previous one. Mainly, the extension comes from value–enhancing action and devaluation process.

8. Distributed Barter-Based Directory Services (CCIA 2008)

   In this paper bartering mechanisms in a real application were applied.

These papers are available at:

`http://www.lsi.upc.edu/~dconrado/`

or by looking for David Cabanillas on the department website. Table 9.1 summarises the relationship between publications and thesis' chapters.

In order to increase the access and visibility of this work, this thesis will be introduced into TDX Server (Tesis Doctorals en Xarxa) and a summary will be published on Nodes ACIA report.

9.2 Conclusions

The results of this thesis demonstrate the relevance of bartering. The following conclusions refer to barter experiments:

- The adoption of decentralisation as a paradigm, allows the distribution of functionalities across the participants providing advantages but at the same time distributing the control. Turning an unique centralised manager into one where none of the participants has the control of the whole system.

- The free will of decision makers and the lack of information has a deep impact in the performance.

- Social modelling: The main criteria for P2P networks is to be *efficient* by having a large number of agents competing for different items. More important than *altruism* is *free market competition* (i.e. large number of agents competing for different items). Altruism is only necessary when many participants want the same item because competition for the same item, causes the coincidence of wants to go down.

- In P2P file sharing, due to the environments properties (i.e. selfish and free–ride behaviours) a bartering mechanism is used amongst the clients who are downloading the same file, which introduces a level of fairness into the system. Trading Paperclips is a new example where bartering is revealed as useful a powerful way of exchange.

- An altruistic society works better than a selfish society. However, by means of bartering scenarios we have shown that in selfish societies:
  - It is possible to achieve good performance depending on the conditions in the market.
  - Barter improves the participants' involvement in the exchange and the society as whole.

- Self–organisation: In a market approach the self–organisation is awareness in the content distribution. From an initial distribution by means of bartering and taking local decisions, the system goes from this initial random distribution to a distribution where the aim is for each participants get the items that they want. For example, BitTorrent empirically selects the peers that offer the best upload and download rates to trade with (i.e. tit–for–tat strategy). The protocol has the ability to self–organize by letting each peer select dynamically which other peers to cooperate with over time.

The final conclusion is that barter is still relevant in the modern world. There are many examples of such re–discovery in the Internet context, in the real and literature world:

- Examples of online social bartering network such as Commuto[1], Trade a Favor[2] and many others where members can exchange in person with others members.

[1] Commuto in www.commuto.com
[2] Trade a Favor in www.tradeafavor.com

- Corporate barter was a major element of the badly functioning Russian economy of the 1990s. Roughly 50% of Russian industrial sales in 1998 were barter transactions. Explanations for the vast scale of barter include liquidity constraints, implicit government subsidies, and managerial rent–seeking.

- The book The People of Sparks by Jeanne DuPrau (the author of The City of Ember) shows how a rustic community uses barter for the exchange of goods and services.

This thesis underpins shows the opportunities of bartering by means of three relevant scenarios. Analysing the oldest method of trade within the context of a new paradigm where everyone is connected, showing that bartering has a great potential, but there are many challenges that can affect the realistic application of bartering that should be studied.

9.3 Future Work

Following the investigations described in this thesis, there are a wide range of further subjects to work on:

- The use of ontologies: How could an agent manage and exploit the knowledge on a given domain to deal with such semantic information and optimise exchanges?[147]
  - The use of a logical language to express agent preference.
  - Logic–based utility functions that allows to evaluate the semantic similarity between items.

- The addition of learning mechanisms: In order to decide on best participant to deal with and the best time to exchange. Deploying opportunistic *GDA*s, agents that can predict future price movements for stocks and commodities through observing and analysing past and current market trends.[133]

- Looking up process and cost – to establish some balance or mechanism to obtain the best balance between the cost to discover good trading and the benefit obtained with the trade.

- To integrate distributed trust and reputation systems in order to apply these systems in environments where the set of peers is large and dynamic, the probability that any two peers interacts decreases.

- An important aspect of electronic commerce is that often trust is absent [176], since it is often difficult for a user to figure out who to trust in online communities. To study how to include trust/reputation in bartering environments.

- To extend market scenarios. For example to have a set of items for an agent could be considered more valuable than to have only some parts (e.g. chapters of some series), copies.

- To improve the propagation mechanism proposed.

- The study of interested–based communities. Participants that in one cluster share a subset of common items and are likely to be of interest to other popular items in the cluster.

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Index

Glossary

Altruism The opposite of selfishness; the practice of cooperating with anyone asking for help. Also known as unconditional cooperation. We regard altruism as irrational in the sense that altruists do not attempt to maximize their benefit.

Arbitrage and Speculation Taking large risks, especially with respect to trying to predict future trades. Speculation and trades are in some cases so closely allied that it is impossible to say at what precise point trade ends and speculation begins. Speculation and arbitrage are very common in the Internet Age, and betting exchanges and Massive Multi–player Online Role–Playing Games (MMORPGs) are examples..

Assignment problems Deals with optimal pairing or matching of objects in two distinct sets.

Autonomous behavior In P2P and MAS systems, independence is an important design parameter. Peers and agents may join and leave the system at any time. In addition, peers that are part of the system may dynamically tune their rates of contribution and consumption. System functionality does not rely on any one specific peer and the P2P system as a whole adapts to this dynamic behaviour of its components.

Bartering The exchange of products and/or services without the use of money. Also called exchange.

Centralized and Decentralized Terms used to describe a system's architecture and implementation. A centralized architecture relies on an authority by definition. In a decentralized architecture no authority exists.

Centralized weighted matchings Gabow gives an $O(|V||E|+|V|^2\ log\ |V|)$ time algorithm, computing the maximum weighted matching. Both return an exact solution, as opposed to approximations.

Collective utility function A social welfare ordering. For example, the idea of aiming at maximizing the sum of all utilities for the members of a society is a *utilitarian concept*. However, this is not the only approach, the *egalitarian social welfare* has as an aim to maximize the welfare of its weakest member. This approach could be used for example in the community of lecturers at a university department. Another approach could be to find a *popular matching*, or a matching that is preferred by a majority of agents to any other matching.

Community A set of entities that use a specific peer–to–peer application in order to contribute and consume a resource. A successful community is a community that generates positive social welfare over time. A successful community can, however, contain at any one time a mixture of dissatisfied entities and satisfied entities.

Complexity The economy may be described as a complex adaptive system, i.e. a system where complexity arises because of the way a large number of agents interact. Complexity thus stems from the fact that the economy is a large composite system. What we observe as the economy is the result of millions of agents interacting.

Cooperation The act of working or acting together to achieve a common goal. Cooperation occurs when the actions of each agent satisfy either or both of the following conditions:

- The agents have an explicit or implicit goal in common, which no agent could achieve in isolation. Their actions tend to achieve this goal.
- The agents perform actions which enable or achieve not only their own goals, but also the goals of agents other than themselves.

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Directory services A directory services is a software application that stores and organizes information about a computer network's users and network resources, and that allows network administrators to manage users' access to the resources. Additionally, directory services act as an abstraction layer between users and shared resources.

Double coincidence of wants Jevons (1893): "The first difficulty in barter is to find two persons whose disposable possessions mutually suit each other's wants. There may be many people wanting, and many possessing those things wanted; but to allow of an act of barter there must be a double coincidence, which will rarely happen.".

Economic system Consider an economic system for coordinating robots. An economy is nothing more than a population of agents (i.e., citizens) producing a global output. The agents coordinate with each other to produce an aggregate set of goods. Centralized economies, such as socialist/communist systems, suffer from an inability to gather all salient information, uncertainty in how to optimize it, and unresponsiveness to changing conditions. Additionally, since economic output is divided equally amongst the entire population, individuals have little incentive to work harder or more efficiently than what is required to minimally comply with the economic plan. Individual input is de-coupled from individual output. The net effect is a sluggish, brittle, inefficient economy.

Free rider A participant that takes advantage of the system, exploiting the effort of other participants, e.g. searching for files or downloading desired content, without any contribution in terms of tasks performed or resources shared.

Incentive technique An incentive technique is any aspect of a system's operation that directly addresses user selfishness and rationality by giving the users the right incentives to complete an action they would otherwise consider costly and, being rational, would try to avoid. Incentive techniques usually assume that the software and hardware modules that implement the functionality of the system cannot be trusted to follow the designer's specifications because selfish peers may find ways to alter this functionality if it is in their interest. We always assume that the (benevolent) designer has the goal of maximizing social welfare in mind.

Matching Matching is the part of economics that focuses on the question of who gets what, particularly when the scarce items to be allocated are heterogeneous and indivisible.

Pareto optimal A Pareto optimal outcome is one where no–one could be made better off without making someone else worse off.

Price of anarchy The tension between private incentives that encourage opportunistic behaviour and the common good that comes from cooperation is a central feature of human interaction.

Prisoner's dilemma In game theory, the prisoner's dilemma is a type of non–zero–sum game in which two players may each cooperate with or defect from the other player. In this game, as in all game theory, the only concern of each individual player is maximizing his/her own payoff, without any concern for the other player's payoff.

Resource The service that a community provides to its members. Members acting as consumers consume the service (at a benefit to themselves) and members acting as contributors contribute the service (at a cost to themselves). Members may be to both contributers and consumers..

Resource discovery It is the process of binding specific resources to an abstract description of the services required for a particular user or program.

Risk A model is ultimately used to anticipate the opponent agent's decisions, or to simulate its actions. If, however, the model is not entirely accurate, then relying on its predictions may harm the agent's performance rather than improving it. Note that even in the unlikely event that the agent possesses an exact model of its opponent, utilizing it will not guarantee an exact prediction due to the limited simulation resources available during a real interaction. Agents in a competitive interaction can greatly benefit from adapting to a particular adversary, rather than using the same general strategy against all opponents.

Scale free networks The term *scale–free* refers to any functional form $f(x)$ that remains unchanged to within a multiplicative factor under a re–scaling of the independent variable x.

Self–organization Decentralized system architecture, where no authorities exist, not even to assist participants who first join the system/community.

Selfishness (or self-interest) The rational practice of community members who avoid helping others in an attempt to minimize their costs. In the terminology based on Trivers and Wilson, an act is said to be altruistic if it is costly to perform but confers a benefit on another individual.

Simple distributed weighted matchings In this approach instead of sending the input, the network topology as a weighted graph, to a central processor, we let all the vertices of the network participate in the computation themselves. By only allowing the vertices to communicate with their direct neighbours in the graph, we keep the locality of the original problem.

Social welfare The benefit of an action is a non–negative number that conveys the amount of satisfaction received by performing the action. The cost of an action is a non-negative number that conveys the amount of dissatisfaction received by performing the action. Social welfare is the sum of the net benefits of a communities members.

The shadow of the future The possibility of future interactions allows credible retaliations against opportunistic behaviour and casts *the shadow of the future* in every decision. The theory of infinitely repeated games studies cooperation under the shadow of the future and provides a more realistic representation of everyday interactions.

Zipf's law Web requests from a fixed user community are distributed according to Zipf's law. Glassman was perhaps the first to use Zipf's law to model the distribution of web page requests.