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RESOURCE ALLOCATION  
VIA  
COMPETING MARKETPLACES

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A thesis submitted to the University of Birmingham for the degree  
of  
DOCTOR OF PHILOSOPHY

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February 2011

UNIVERSITY OF  
BIRMINGHAM

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## Abstract

This thesis proposes a novel method for allocating multi-attribute computational resources via competing marketplaces. Trading agents, working on behalf of resource consumers and providers, choose to trade in resource markets where the resources being traded best align with their preferences and constraints.

Market-exchange agents, in competition with each other, attempt to provide resource markets that attract traders, with the goal of maximising their profit.

Because exchanges can only partially observe global supply and demand schedules, novel strategies are required to automate their search for market niches. By applying a novel methodology, which is also used to explore, for the first time, the generalisation ability of market mechanisms, novel *attribute-level selection* (ALS) strategies are analysed in competitive market environments. Results from simulation studies suggest that using these ALS strategies, market-exchanges can seek out market niches under a variety of environmental conditions.

In order to facilitate traders' selection between dynamic competing marketplaces, this thesis explores the application of a reputation system, and simulation results suggest reputation-based market-selection signals can lead to more efficient global resource allocations in dynamic environments. Further, a subjective reputation system, grounded in Bayesian statistics, allows traders to identify and ignore the opinions of those attempting to falsely damage or bolster marketplace reputation.



*This thesis is dedicated to the loving memory of Peggy Robinson.*

*You were right, the hard work did pay off.*

*If nothing is going well, call your grandmother.  
—Italian proverb.*



## 🌀 Acknowledgments 🌀

First and foremost I gratefully acknowledge the guidance provided by my supervisor, Professor Xin Yao, during these last three years. Throughout my research, he has always offered useful advice, pushed me to critically assess my work and, I believe, shaped me into a better researcher. Secondly, I wish to offer my sincerest thanks to Professor Peter McBurney. Peter has been an excellent collaborator for the last couple of years, and I can only hope to work with him again. Generous time, support and encouragement has been offered by the members of my Thesis Group: Dr Jon Rowe and Dr John Bullinaria. The biannual Thesis Group meetings always left me buoyant and ready to get stuck in some more; I owe them both thanks.

\* \* \*

I have spent a significant amount of time working closely with the following three colleagues, and now great friends: Dr Peter Lewis, Arjun Chandra and Vivek Nallur; always eager, and never reticent about expressing their views, working with them has always been a pleasure. As well as the three above, getting through this process would have been a lot harder without having had the privilege of spending quality time on the football pitch, or in the pub, with the following people: Dr Dave Brooks, Dr Anh Dinh, Dr Dan Ghica, Dr Nick Hawes, Dr Ben Jones, Dr Rob Minson, Dr Philipp Rohlfshagen and Dr Andrea Soltoggio. I couldn't have asked for better people to work with. I truly couldn't.



A massive thanks to the whole Budgen gang—Kate and Jamie, and especially Penny and Keith, who have provided me with not only a roof over my head and hot meals on the table, but with love and support; I feel blessed and a part of your family. And to my immediate family, how lucky I am to have you all. This thesis is the end result of a seven year academic journey, which would have been so much harder to complete without your help. Thanks Grandad, Nan and Alan for all the encouragement you gave me, and Helen and Harry, I'm quite confident you're the best siblings in the world. Of course, I wouldn't have achieved so much if it wasn't for two truly outstanding parents: thank you so much Mum and Dad, for *everything* you have done and provided for me.

\* \* \*

This process has not been easy, and while it has for the most part been enjoyable and rewarding, I am truly lucky to have had someone special in my life to help me through the tough times. I save my last and most sacred thanks for my future wife, Molly. This thesis wouldn't exist without you. You are truly beautiful, in every way.

*A journey is best measured in friends, rather than miles.*  
—Tim Cahill

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# CONTENTS

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<b>1</b>	<b>Introduction</b>	<b>1</b>
1.1	Scenario . . . . .	2
1.2	Research Questions . . . . .	4
1.3	Thesis Contributions . . . . .	5
1.3.1	Publications . . . . .	7
1.4	Thesis Outline . . . . .	7
<b>2</b>	<b>Background and Related Work</b>	<b>11</b>
2.1	Agent-based Computational Resource Allocation . . . . .	13
2.1.1	Utility computing . . . . .	14
2.1.2	Software agents as economic actors . . . . .	16
2.1.3	Computational resource allocation desiderata . . . . .	18
2.2	Market-based Mechanisms for Multi-attribute Resource Allocation	20
2.2.1	Centralised approaches . . . . .	22
2.2.2	Decentralised approaches . . . . .	24
2.2.3	Problems with existing approaches . . . . .	25
2.3	Double Auctions . . . . .	27
2.3.1	Double auction basics . . . . .	28
2.3.2	Continuous double auctions . . . . .	30
2.3.3	Multi-attribute double auction approaches . . . . .	32

2.3.4	Commodifying multi-attribute resources . . . . .	34
2.4	Competition Between Marketplaces . . . . .	38
2.4.1	Approaches to double auction marketplace design . . . . .	39
2.4.2	Analysing competing marketplaces . . . . .	41
2.4.3	Generalisation and robustness issues . . . . .	43
2.5	Trust and Reputation Issues in Open Electronic Markets . . . . .	44
2.5.1	Notions of trust and reputation . . . . .	46
2.5.2	Trust and reputation approaches in electronic markets . . . . .	48
2.6	Summary and Conclusions . . . . .	50
<b>3</b>	<b>Generalisation Properties of Competing Marketplaces</b>	<b>53</b>
3.1	Motivation and Research Questions . . . . .	55
3.2	The TAC Market Design (CAT) Competition . . . . .	58
3.3	Empirical Evaluation of Entries' Generalisation Ability . . . . .	60
3.3.1	General experimental setup . . . . .	62
3.3.2	Evaluation of the 2008 competition . . . . .	63
3.3.3	Evaluation of the 2009 competition . . . . .	70
3.3.4	Evaluation of best performers and overall progress . . . . .	71
3.3.5	Discussion . . . . .	74
3.4	Conclusions . . . . .	75
<b>4</b>	<b>A Model for Computational Multi-attribute Resource Allocation</b>	<b>81</b>
4.1	Computational Resource Allocation . . . . .	83
4.1.1	Trading resources in distributed marketplaces . . . . .	85
4.2	Decision Making Models for Agents . . . . .	87
4.2.1	Trader multi-attribute utility functions . . . . .	87
4.2.2	Market-exchange payoff function . . . . .	90
4.2.3	Resource allocation payoff examples . . . . .	91
4.3	Market-exchange Agent Mechanics . . . . .	98
4.3.1	Double auction policies . . . . .	100

4.4	Trading Agent Mechanics . . . . .	102
4.4.1	The Zero-Intelligence Plus trading strategy . . . . .	103
4.4.2	Integrating market fees . . . . .	107
4.4.3	Market-selection strategy . . . . .	108
4.5	An Algorithm for Measuring Allocative Efficiency . . . . .	111
4.5.1	Calculating an allocation's utility . . . . .	112
4.5.2	The Hungarian Algorithm for assignment problems . . . . .	114
4.5.3	Multi-attribute resource assignment problems . . . . .	115
4.6	Conclusions and Discussion . . . . .	118
<b>5</b>	<b>Mechanisms for Market Niching</b>	<b>121</b>
5.1	Motivation . . . . .	123
5.1.1	Automatic market niching . . . . .	124
5.1.2	Research questions . . . . .	126
5.2	Attribute-level Selection Strategies . . . . .	126
5.2.1	Attribute-level selection as a bandit problem . . . . .	128
5.2.2	Attribute-level selection as an optimisation problem . . . . .	132
5.3	Defining Environmental Contexts . . . . .	134
5.3.1	Representative trader contexts . . . . .	135
5.3.2	Possible charging contexts . . . . .	142
5.4	Attribute-level Selection Strategy Performance . . . . .	144
5.4.1	Experimental setup . . . . .	146
5.4.2	Results and analysis . . . . .	148
5.5	Market Niching in Multi-niche Environments . . . . .	160
5.5.1	'Constraint-induced niches' environments . . . . .	162
5.5.2	'Preference-induced niches' environments . . . . .	167
5.5.3	Summary . . . . .	170
5.6	Conclusions and Discussion . . . . .	172

<b>6</b>	<b>Improved Resource Allocations Using Subjective Reputations</b>	<b>175</b>
6.1	Motivation . . . . .	177
6.1.1	Research questions . . . . .	179
6.2	A Bayesian Reputation Approach . . . . .	180
6.2.1	Representing trust with Beta distributions . . . . .	181
6.2.2	Combining opinions to form reputations . . . . .	184
6.2.3	Making market-selection decisions using trust and reputation	186
6.3	Modelling Uncertain Market-based Environments . . . . .	187
6.3.1	Noisy recommenders . . . . .	188
6.3.2	Lying recommenders . . . . .	189
6.3.3	Trader churn . . . . .	192
6.4	A Subjective Reputation Approach for Uncertain Environments .	193
6.4.1	Recommendation weights for trader opinions . . . . .	193
6.4.2	Learning recommendation weights . . . . .	195
6.5	An Empirical Analysis of Reputation Approaches . . . . .	199
6.5.1	The effects of trader churn on system performance . . . . .	199
6.5.2	Dealing with noisy recommenders . . . . .	204
6.5.3	Dealing with lying recommenders . . . . .	210
6.5.4	Recommender Network analysis . . . . .	212
6.6	Conclusions and Discussion . . . . .	219
<b>7</b>	<b>Conclusions</b>	<b>223</b>
7.1	Summary of Thesis Contributions . . . . .	226
7.2	Future Work . . . . .	229

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# LIST OF FIGURES

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2.1	An example of a simple double-auction <i>order book</i> ; the clearing price is determined by the lowest (highest) matchable bid (ask). . . . .	29
2.2	Example <i>supply</i> and <i>demand</i> curves for a market. The intersection of these curves determines the both the equilibrium <i>price</i> and <i>quantity</i> . . . . .	31
4.1	Resource valuations for a buyer and seller without preferences or maximum constraints over attributes, for different <i>resource types</i> . . . . .	94
4.2	Resource valuations for a buyer and seller where the buyer has a maximum constraint on resource's attributes, for different <i>resource types</i> . . . . .	96
4.3	Resource valuations for a buyer and seller with preferences over different resource attributes, for different <i>resource types</i> . . . . .	99
5.1	Maximum theoretical daily total trader profit for a randomly generated <i>unconstrained single niche</i> trader context. . . . .	137
5.2	Maximum theoretical daily total trader profit for a randomly generated <i>constrained single niche</i> trader context. . . . .	138
5.3	Maximum theoretical daily total trader profit for a randomly generated <i>constraint-induced niches</i> trader context. . . . .	140

5.4	Maximum theoretical daily total trader profit for a randomly generated <i>preference-induced niches</i> trader context. . . . .	142
5.5	Simulation profit distributions for competing market-exchanges using different ALS strategies in the <i>bid/ask spread commission</i> charging context. . . . .	152
5.6	Typical behaviour of <i>Softmax</i> and <i>1+1 ES</i> ALS strategies when involved in simulations using the <i>unconstrained single niche</i> trader and <i>market registration fee</i> charging, contexts. . . . .	152
5.7	Typical behaviour of <i>Softmax</i> and <i>1+1 ES</i> ALS strategies when involved in simulations using the <i>unconstrained Single Niche</i> trader and <i>transaction fee</i> charging, contexts. . . . .	154
5.8	The number of wins managed by each of the ALS strategies for the <i>unconstrained single niche</i> trader context. . . . .	155
5.9	The number of wins managed by each of the ALS strategies for the <i>constrained single niche</i> trader context. . . . .	159
5.10	Heat maps showing the niching ability of various strategies for simulations involving the <i>transaction price fee</i> charging and <i>constraint-induced niches</i> trader, contexts. . . . .	164
5.11	Typical niching behaviour of several ALS strategies when in competition during simulations using the <i>transaction price fee</i> charging and <i>constraint-induced niches</i> trader, contexts. . . . .	166
5.12	Heat maps showing the niching ability of various strategies for simulations involving the <i>bid/ask spread commission</i> charging and <i>preference-induced niches</i> trader, contexts. . . . .	169
5.13	Typical niching behaviour of several ALS strategies when in competition, during single simulations using the <i>bid/ask spread commission</i> charging and <i>preference-induced niches</i> trader, contexts. . . . .	171
6.1	The effect of different time discounting factors on beta distributions representing interaction histories. . . . .	184

6.2	An example of how combining beta distributions is a matter of aggregating the $\alpha$ and $\beta$ parameters of the relevant distributions. . .	185
6.3	Collections of beta distributions <i>weighted</i> according to recommendation weights ( $\hat{\gamma}$ ). . . . .	198
6.4	Overall mean system allocative efficiency for varying levels of trader churn. . . . .	202
6.5	Given the overall mean system utility, as measured in profits, this figure shows the <i>proportion</i> of total system profits kept by the trader population. . . . .	204
6.6	Mean system allocative efficiency for simulations involving varying levels of <i>noisy recommenders</i> in the trader population. . . . .	207
6.7	Incremental change in allocative efficiency experiments with increasing proportions of noisy recommenders. . . . .	208
6.8	Mean frequency of recommender connections maintained between different <i>cohorts</i> of traders. . . . .	209
6.9	Mean allocative efficiency for simulations involving various levels of lying recommenders that are using the <i>Supply and Demand Attack</i> . . . . .	211
6.10	Incremental change in allocative efficiency gets worse with an increase in the proportion of lying recommenders. . . . .	212
6.11	Mean frequency of recommender connections maintained between different cohorts of traders in simulations where there are varying proportions of lying recommenders. . . . .	213
6.12	<i>In-degree</i> frequency density functions for the <i>Favourite Recommender Graph</i> and the <i>Random Recommender Graph</i> , built from a recommendation network graph taken from a typical simulation. . . . .	216
6.13	A visualisation of a typical Favoured Recommender Graph from a simulation using a <i>constraint-induced niches</i> trader context, at a single point in time. . . . .	218



6.14	A visualisation of a typical Favoured Recommender Graph from a simulation using a <i>preference-induced niches</i> trader context, at a single point in time. . . . .	220
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# LIST OF TABLES

---

2.1	A fictional example of eight different option contract variations for the same underlying asset. . . . .	35
2.2	Six different <i>Amazon EC2 Instance Types</i> . Each row represents a different type of computational resource offered on-demand by Amazon web services. . . . .	37
3.1	Mean, standard deviation, rank and $\hat{\delta}$ values for a set of tournaments using the <i>just-GD</i> trader context and a set of tournaments using the <i>no-GD</i> trader context. First presented in [145]. One mean, for IA-08 and italicised was found to be from a non-normally distributed sample. However, it was not necessary to subject it to a statistical comparison with any other sample for the analysis carried out in this chapter. . . . .	64
3.2	Mean, standard deviation, rank and $\hat{\delta}$ values for a set of tournament repetitions using the <i>just-ZIC</i> trader context, and a set of tournaments using the <i>no-ZIC</i> traders context. First presented in [145]. . . . .	65
3.3	Mean, standard deviation, rank and $\hat{\delta}$ values for a set of tournament repetitions using the <i>just-ZIP</i> trader context, and a set of tournaments repetitions using the <i>no-ZIP</i> trader context. First presented in [145]. . . . .	67

3.4	Mean, standard deviation, rank and $\hat{\delta}$ values for a set of tournament repetitions using the <i>all specialists</i> competitor context, and a set of tournaments using the <i>top three</i> competitor context. . . . .	68
3.5	Mean, standard deviation, rank and $\hat{\delta}$ values for a set of tournament repetitions using the <i>all specialists</i> competitor context, and a set of tournaments repetitions using the <i>bottom five</i> competitor context. . . . .	69
3.6	Mean, standard deviation, rank and $\hat{\delta}$ values for a set of tournament repetitions using the short-early scoring context and a set of tournament repetitions using the medium-middle scoring context. . . . .	70
3.7	Mean, standard deviation, rank and $\hat{\delta}$ values for a set of tournaments using entrants to the 2009 CAT Tournament, with an environment containing just GD and no GD traders. First presented in [146]. . . . .	71
3.8	Mean, standard deviation, rank and $\hat{\delta}$ values for a set of tournament repetitions using the just-RE trader context and a set of repetitions using the no-RE trader context. . . . .	72
3.9	Mean overall specialist performance from tournaments using various trader contexts. . . . .	73
4.1	In the ZIP algorithm, the bounds for uniform distributions are adjusted according to whether the algorithm wishes to raise or lower its shout price. . . . .	105
5.1	Default parameters used in all simulations unless otherwise stated within the text. All parameters remain fixed for the duration of each simulation. . . . .	149
5.2	Mean <i>simulation profit</i> over 50 simulation repetitions for market-exchanges using various ALS strategies, when the environmental context comprises the <i>bid/ask spread commission</i> charging and <i>unconstrained single niche</i> trader, contexts. . . . .	150

- 5.3 Mean *simulation profit* over 50 simulation repetitions for market-exchanges using various ALS strategies, when the environmental context comprises the *registration fee* charging and *unconstrained single niche* trader, contexts. . . . . 153
- 5.4 Mean *simulation profit* over 50 simulation repetitions for market-exchanges using various ALS strategies, when the environmental context comprises the *transaction price fee* charging and *unconstrained single niche* trader, contexts. . . . . 154
- 5.5 Mean *simulation profit* over 50 simulation repetitions for market-exchanges using various ALS strategies, when the environmental context comprises the *bid/ask spread commission* charging and *constrained single niche* trader, contexts. . . . . 157
- 5.6 Mean *simulation profit* over 50 simulation repetitions for market-exchanges using various ALS strategies, when the environmental context comprises the *registration fee* charging and *constrained single niche* trader, contexts. . . . . 158
- 5.7 Mean *simulation profit* over 50 simulation repetitions for market-exchanges using various ALS strategies, when the environmental context comprises the *transaction fee* charging and *constrained single niche* trader, contexts. . . . . 158
- 5.8 For each strategy, each data point provides the measure of system-wide mean daily allocative efficiency, over *all* simulations involving each strategy and its competitors. . . . . 163
- 5.9 For each strategy, each data point provides the measure of system-wide mean daily allocative efficiency, over *all* simulations involving each strategy and its competitors. . . . . 168
- 6.1 Three types of charging scheme were split equally across nine market-exchanges. . . . . 201



## CHAPTER 1

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# INTRODUCTION

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## 1.1 Scenario

The significant growth of Internet-enabled devices is accompanied by a continually increasing demand for access to computational resources and services, in order to satisfy an ever growing user base. This is resulting in current *system-centric* approaches to resource allocation becoming limiting [63].

Examples of these approaches include those used to allocate resources within paradigms such as cloud and grid computing, which often rely on omniscient centralised mechanisms with full knowledge of the resources under control.

Concomitant to this technological growth, the biggest untapped source of computational power is now likely to be the combined distributed resources of individual user machines, distributed across space and time and connected by commonplace high-speed Internet connections. Added to this, when one considers that most of these resources will be sitting idle for long periods of time [124], designing economic mechanisms for incentivising the provision of these excess resources, and then allocating them to users who desire them most, becomes of interest.

Market-based approaches [30], have been suggested as a way to efficiently allocate resources between competing self-interested agents in distributed settings [35, 63]. Within this field, the domain of *Mechanism Design* concerns itself with the design of market mechanisms whose resource allocations satisfy certain designer-specified objectives, for example that allocations are economically efficient, by maximising the total utility surplus across all agents. While theoretical approaches have resulted in mechanisms that satisfy several desirable properties in restricted settings, often these approaches are not practical for the design of market mechanisms in more open real-world environments.

Instead, considerable attention has been given to the *empirical* design and analysis of market mechanisms [31, 136], often using agent-based approaches [183] to create rich coevolutionary simulation models of market-based systems

## 1.1. SCENARIO

[118]. Particular attention has been given to the study of the *Double Auction* market mechanism using these approaches because it allocates distributed resources efficiently under a wide range of settings [33], and theoretical analysis is impractical in all but the most restricted of cases [59]. Significant attention has been given to the study of competing double auction marketplaces [174, 160, 132, 117], and the impact their competition has on allocations of single-attribute resources (commodities) [23].

However, computational resources are complex multi-attribute resources, and resource consumers and providers tend to have different preferences and constraints over attributes. This can make allocating computational resources efficiently challenging, and little attention has been given to studying double auction approaches to achieving this. With that in mind, this thesis considers a novel approach for allocating multi-attribute computational resources using multiple competing double auction marketplaces. Within such an approach, multiple market-exchange agents each provide double auction markets for particular *types* of resources, that is, each resource exchanged within the same market has the same attribute values. Trading agents, working on behalf of resource consumers and providers, are expected then to select between markets depending on which type of resource most suits their preferences and constraints at the present time, while marketplaces, in competition with each other, are expected to select the types of resources to be traded within their market that most satisfy *market segments* within the trader populations.



## 1.2 Research Questions

This thesis is concerned with the design and empirical analysis of market mechanisms for the allocation of distributed multi-attribute computational resources, within environments where resource consumers and providers have potentially different preferences and constraints over resource attributes, and market mechanisms are unaware of these *a priori*.

In general, the overarching research questions that this thesis considers are:

- How can multi-attribute computational resources be allocated within distributed environments which use multiple market mechanisms?
- How can we better design mechanisms that perform well within such models of resource allocation? Further, how can we improve the mechanism design and analysis process to more carefully consider the generalisation properties of these mechanisms?

The method of study used within this thesis is inspired by empirical approaches taken within similar domains, such as for the study of double auction market mechanisms in isolation, e.g., the JASA simulation framework [76], or double auction market mechanisms in competition, e.g., the JCAT simulation framework [24]. In the same spirit, the research questions posited above are studied within a rich agent-based simulation environment, specifically developed to model both the competition between consumers and providers over multi-attribute resources, and the competition between marketplaces over traders that potentially have very different preferences and constraints over resource attributes. The outcome of simulations of these rich agent-based models of competitive behaviour is a complex coevolutionary market-based system, where agents learn over time. As such, care is taken when analysing this system, by using appropriate statistical and computational methods wherever necessary. Analysis within this model is done in both a qualitative and quantitative context. Quantitatively, metrics

### 1.3. THESIS CONTRIBUTIONS

including: the economic efficiency of resource allocations across the system; the profits that marketplaces generate by fees levied on traders; or the profits made by traders from the buying and selling of resources, are used to measure the impact of various mechanisms. Qualitatively, considerable thought has been given to helping the reader *visualise* behaviours within this complex market-based system, using a variety of visualisation techniques.

## 1.3 Thesis Contributions

The main contributions of this thesis are:

- A novel methodology for measuring the generalisation properties of competing market mechanisms in coevolutionary trading environments, and an application of the methodology to market mechanisms submitted to TAC Market Design Competitions, demonstrating its effectiveness.
- A novel approach to the allocation of multi-attribute computational resources within distributed environments, relying on multiple competing marketplaces satisfying market segments by running markets for certain types of computational resource.
- The formulation of trader decision-making models for valuing multi-attribute computational resources and reasoning over these marketplaces, as well as a method for determining the optimal allocation of computational resources between these traders.
- The first clear formulation of the *automatic niching problem*, which presents itself when marketplaces must decide what type of resource market to offer to traders with unknown resource preferences and constraints.
- An analysis of the effectiveness of two approaches for tackling the automatic niching problem, using the previously developed methodology to

measure performance in a variety of environments they are expected to operate in.

- The first application of a reputation-based approach for facilitating selection between double-auction marketplaces by integrating reputation information into market-selection strategies.
- An analysis of the performance of reputation-based approaches to market-selection, demonstrating that subjective reputation information improves market-selection decisions, which leads to more efficient allocations globally.

The approach to resource allocation presented within this thesis does not require the presence of an omniscient central resource allocator, or the solving of computationally expensive optimisation problems, in order to allocate multi-attribute resources. The distributed nature of multiple competing marketplaces often results in several different types of resource market, from which traders can migrate to the one that most satisfies their preferences and constraints; this behaviour does not require any coordination between marketplaces. While directly comparing this approach to other methods of multi-attribute resource allocation is not within the scope of this thesis, this approach is certainly *suitable* for allocating distributed computational resources, because it satisfies a number of desirable properties that other approaches do not.

One of the themes underlying this thesis is generalisation and robustness, and the contributions made throughout concern themselves, directly or indirectly, with attempting to improve the generalisation and robustness of both market and trader mechanisms, by designing mechanisms that perform well in a variety of representative environments, not merely randomly generated instantiations. This is supported by the application of a novel methodology to the assessment of some of these mechanisms, which is also shown to, when applied to market mechanisms previously championed in the literature, find they are brittle to

#### 1.4. THESIS OUTLINE

several environmental situations. Another theme within this thesis involves competition between marketplaces, and research within this thesis concerns itself with exploring different aspects of competition between market mechanisms. In general, it is hoped that the methods developed for analysing the performance of mechanisms under competition, within this thesis, can be used by anybody who is interested in empirically analysing competition between marketplaces, be it from a computer science, economics, or marketing, perspective.

##### 1.3.1 Publications

The following publications have arisen out of work carried out within this thesis.

- [145] E. Robinson, P. McBurney and X. Yao “How specialised are specialists? Generalisation properties of entries from the 2008 TAC Market Design Competition,” in *proceedings of the 2009 Trading Agent Design and Analysis Workshop (TADA 2009)*, IJCAI 2009, 2009.
- [146] E. Robinson, P. McBurney and X. Yao “How specialised are specialists? Generalisation properties of entries from the 2008 and 2009 TAC Market Design Competitions,” *Agent-Mediated Electronic Commerce: Designing Trading Strategies and Mechanisms*, volume 59 of *Lecture Notes in Business Information Processing*, pp. 178–194, Springer, 2010.

Further, work from chapters 5 and 6 is being prepared for submission to relevant journals.

## 1.4 Thesis Outline

The remainder of this thesis progresses as follows. Beginning in Chapter 2, the concept of computational resource allocation within a distributed utility computing model is introduced, and future resource allocation issues are highlighted, with particularly reference to the current limiting *system-centric* approaches. The chapter considers a variety of current market-based approaches for allocating multi-attribute resources, and highlights the unstudied approach

considered within this thesis, of allocating computational resources using competing double auction marketplaces.

Chapter 3 builds on gaps in the literature identified in Chapter 2. Specifically, it highlights that current methods for analysing and measuring the performance of market mechanisms in competitive environments have not given much attention to the *general* performance of market mechanisms across a variety of environmental situations. Within the chapter, a methodology for measuring, both quantitatively and qualitatively, the generalisation ability of double auction market mechanisms is presented; application of this methodology to a variety of market mechanisms within CAT tournaments demonstrates that many are not robust against a number of environmental changes.

In Chapter 4 a novel model for allocating computational resources via competing double auction marketplaces is developed. In contrast to similar models that deal with single-attribute resources, this model considers the allocation of multi-attribute resources, and qualitative differences between the models presents new challenges in the form of requiring new mechanisms. Firstly, decision-making models appropriate for determining preferences over the multi-attribute computational resources are developed, based upon marketing models grounded in consumer theory. Using the multi-attribute utility trader models, visualisations of trader payoffs for various resource types, demonstrate the challenges that marketplaces face in locating the popular market niches across a variety of trader contexts. Because typical methods for calculating the allocative efficiency of resource allocations in single-attribute models are not appropriate for the multi-attribute resources considered in this model, a new algorithm is developed for making this calculation that allows the allocative efficiency of the approach to be measured in simulations throughout the thesis.

Chapter 5 tackles the main research challenge noted in Chapters 2 and 4, viz., how competing market-exchanges can automatically locate market niches that satisfy segments of a trader population. To that end, the *automatic niching*

#### 1.4. THESIS OUTLINE

*problem* is described, and several *attribute-level selection* (ALS) strategies are proposed to tackle this problem, based upon n-armed bandit and evolutionary optimisation, approaches. A comprehensive computational study is carried out to assess the performance of these strategies by applying the methodology developed in Chapter 3 within the market-based model developed in Chapter 4. In general, simulation results show that several strategies are able to automatically locate market niches within a variety of environmental settings, and that in many cases competing marketplaces can self-organise to cover market niches that satisfy all market segments within the environment, leading to desirable allocations.

Chapter 6 complements the automatic market niching mechanisms introduced in Chapter 5 by considering new approaches for trader market-selection over competing marketplaces using niching mechanisms. While reputation approaches have been widely applied in electronic marketplace settings, no work currently addresses the suitability of reputation approaches to signalling the expected behaviour of marketplaces. Highly reputable marketplaces should offer resource markets that traders want to trade in, as well as execute trades that are profitable for traders. Chapter 6 explores how reputation approaches facilitate better trader market-selection decisions, and demonstrates that a subjective reputation approach, grounded in Bayesian statistics, improves traders' market-selection decisions, resulting in more efficient resource allocations globally. Analysis is carried out using agent-based simulations, while an initial investigation studying the influential properties of certain traders is undertaken via a statistical analysis of emergent market-recommendation networks.

Chapter 7 draws conclusions based upon the research carried out within the thesis, reviews the contributions that this thesis has made, and discusses how this work can be extended in the future.



## CHAPTER 2

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# BACKGROUND AND RELATED WORK

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*To know the road ahead, ask those coming back.  
—Chinese proverb*



This chapter introduces problems associated with allocating multi-attribute computational resources, distributed across space and time. It focusses on market-based approaches to computational resource allocation, and highlights the unstudied potential approach of commodifying multi-attribute resources and allocating them via competing double auction marketplaces. Simulation approaches for designing and analysing competing marketplaces are reviewed, and gaps concerning approaches for measuring the general performance of market mechanisms are highlighted. Further, some trust and reputation approaches within electronic markets are reviewed, and it is argued that their suitability for signalling expected marketplace behaviour needs to be further analysed.

The rest of this chapter proceeds as follows. Section 2.1 introduces the notion of computational resources for utility computing and the current *system-centric* models governing their allocation. A distributed model of agent-based computational resource allocation is motivated, and some desiderata concerning such a model are considered, which current system-centric models of resource allocation fail to meet. In Section 2.2 current approaches to *market-based resource allocation* are introduced, focussing on both centralised and fully decentralised mechanisms. The appropriateness of these mechanisms is considered against the requirements for allocating multi-attribute resources in a distributed environment, and it is concluded that none are strictly appropriate for several reasons. The double auction—the market mechanism this thesis focusses on—is introduced in Section 2.3. It is shown, however, that while efficient resource allocations can be achieved with the mechanism, multi-attribute variants are computationally prohibitive, and not scaleable to large systems. At this point in the chapter, the novel approach studied within this thesis is proposed: that multi-attribute resources could be commodified and allocated across multiple markets run by competing market-exchanges. Section 2.4 focusses on empirical models and approaches within the literature for studying resource allocation via

## 2.1. AGENT-BASED COMPUTATIONAL RESOURCE ALLOCATION

competing marketplaces, and concludes that less attention has been given to measuring the *general* performance of market mechanisms, across different environmental settings. Section 2.5 discusses trust and reputation approaches as a means of signalling and sanctioning behaviour in electronic marketplaces. While much attention has been given to the application of reputation approaches in general, almost none has been given to how approaches can be applied to signalling marketplace behaviour in a competitive environment, and what impact it has on resource allocations. Finally, Section 2.6 summarises the chapter, and highlights why the work within this thesis is required.

### 2.1 Agent-based Computational Resource Allocation

A *computational resource* is an abstract term that can refer to either computational hardware, software, or a services composed of both. The consumption of a computational resource involves permitted access to some computational hardware or software for a specified amount of time. Conversely, the provision of computational resources involves temporarily relinquishing access to some hardware or software, by allowing another entity access to it. With the advent of *virtualisation* [7], computational hardware platforms can be carved up into many smaller virtualised resources, each running, for example, an entire operating system—*system virtual machines*—or specific instances of some software—*process virtual machines*.

System virtual machines are typically required less frequently, but for longer periods, while process virtual machines are typically used more frequently but for much shorter periods, and often to run specific tasks. Regardless of the job or function of the computational resource being used, a common feature is that each resource usually has *multiple attributes*. For example, a computational resource in the form of a system virtual machine might be described in terms of its: memory capacity, storage capacity, CPU speed and number of CPU cores.

Alternatively, a computational resource in the form of an image-resizing process virtual machine might be described over its guaranteed availability and image-resizing speed.

### 2.1.1 Utility computing

As Buyya et al. [22] observe, as far back as 1969, UCLA researchers—working on the Internet’s precursor ARPANET—had already begun considering the possibilities that might emerge from a globally connected network of computational devices:

As of now, computer networks are still in their infancy, but as they grow up and become sophisticated, we will probably see the spread of ‘computer utilities’ which, like present electric and telephone utilities, will service individual homes and offices across the country.  
Kleinrock [86, p. 4.]

Much in the same way that water, gas, and electricity are public utilities, *utility computing* refers to the bundling of computational resources into distinguishable units, and then providing those resources *on-demand*; importantly, resources should be made available in a way that allows the consumer to easily adjust their utilisation.

#### The cloud model of utility computing

Within the commercial IT domain, the provision of on-demand computational resources has attracted the attention of major IT vendors, including HP, IBM, Oracle, and Amazon [63]. A new paradigm has emerged—*cloud computing*—which describes the provision of location-independent resources in an on-demand fashion. Resources are allocated to users across the Internet from a *cloud provider*, usually a major IT vendor with a massive and powerful hardware infrastructure. According to Armbrust et al. [4] the main characteristics that separate the cloud computing model from other paradigms are: (i) the appearance

## 2.1. AGENT-BASED COMPUTATIONAL RESOURCE ALLOCATION

of infinite computational resources that scale with the user's demand, known as *elasticity*; (ii) a small barrier to entry because there are no hardware costs; and (iii) the ability to pay for resources on-demand. Based upon these compelling characteristics, the benefits are clear to consumers. However, as Briscoe and Marinos [19] note, there are some fundamental issues with the cloud computing model: (i) because massively centralised hardware infrastructures provide all resources, when there is a failure it is massive and *systemic*; and (ii) because ever decreasing hardware costs mean cloud providers are growing exponentially, resulting in huge environmental impacts and massively under-utilised systems. Briscoe and Marinos argues that these concerns could be overcome by the implementation of a *community cloud*—a cloud provider infrastructure built on top of individuals' computational resources, where both consumers and providers are distributed across the Internet.

### Large-scale distributed computational resources

Combined individual machines, distributed across the Internet, are possibly the biggest untapped computational resource, and many if not most will be sitting idle most of the time [140, 124]. Using *volunteer computing* models, some of this computational power has been utilised in a distributed fashion. For example, the SETI@home [153] and BOINC [15] projects harness users' idle computer time to perform distributed computational tasks. As of January 2011, the combined computational power of BOINC volunteers sits at 4.6 petaFLOPS; currently, the most powerful supercomputer only manages 2.5 petaFLOPS<sup>1</sup>.

Volunteer computing projects explicitly rely on altruism from their user-base, who provide their computational resources for running tasks delegated by a central coordinator. While the economic benefits to consumers within a utility computing model are clear, individual users are only likely to provide resources if there are economic benefits to doing so. Further, among the common

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<sup>1</sup><http://www.bbc.co.uk/news/technology-11644252>

characteristics that any utility computing model should have, Rappa [139]

identifies:

- *reliability*: the service or resource should be available when and where the user needs it;
- *usability*: the service or resource should be simple to use at the point of use, thus integrating into the user's environment easily;
- *utilisation rates*: user demand for the services or resources may vary significantly over time, but there should always be available capacity for users.

Many of these objectives are in practice difficult to achieve, particularly when one considers these desiderata in terms of large-scale, decentralised collections of resources. For a system such as this to work, in a computational and economic sense, it will need to operate without the intervention of human resource owners or users. Therefore, *Software Agents* have been proposed to help solve resource coordination and utilisation problems within these large-scale systems.

### 2.1.2 Software agents as economic actors

According to Wooldridge and Jennings [184] a software agent has the following properties:

- *autonomy*: they operate without the direct intervention of humans or others, and with self-control over their state and actions;
- *social ability*: they are able to communicate and interact with other agents;
- *reactivity*: they perceive their environment and react to changes within it;
- *pro-activeness*: they are not *only* reactive, and can exhibit goal-oriented, deliberative behaviour.

The general role of software agents is to represent, and perform tasks for, their owners. In terms of a distributed utility computing environment, these tasks might include: locating, valuing, and competing over resources, or coordinating processes by which resources can be allocated across agents. As Wooldridge [183,

## 2.1. AGENT-BASED COMPUTATIONAL RESOURCE ALLOCATION

pp. 7-8.] notes, no system is entirely composed of a single agent, and attention is given to the field of *multi-agent systems* from two viewpoints: (i) agents as a paradigm for software engineering; and (ii) agents as a tool for understanding human societies.

*Agent-based Computational Economics* (ACE) [167] takes a *petri dish* approach to modelling economic processes, through the bottom-up interactions of economic agents in a multi-agent system, and is an example of where the second viewpoint has had a powerful impact on the understanding of human economies. The work carried out within this thesis, however, aligns itself more with the first viewpoint. From an engineering perspective, as McBurney and Luck [103] suggest: any large-scale, open and dynamic system needs to adopt the multi-agent systems paradigm, with respect to its design and implementation. An advantage of the multi-agent system approach is that systems can be iteratively engineered *in-vitro* using a wide array of simulation tools, allowing one to immediately see the impact system designs have on both individual and systemic, behaviour. Further, these agent-based approaches often require no more complexity or implementation than necessary to model the individual decision-making behaviours of individual actors within the system.

### **Economic agents**

The term “economic actor” [101] specifically refers to a model of an individual decision maker, typically eschewing non-rational actions, thus always attempting to maximise its utility, which is used as a measure of relative happiness or satisfaction. While at one stage modelling human behaviour in this way was considered reasonable, such simplistic theories have given over to more multidisciplinary concepts, such as *bounded rationality* [156], which is the idea that individuals’ decision making is influenced and limited by other factors, such as the amount of information available and how long it takes to process. However, while economic rationality might be too strong an assumption for

human behaviour in general, it can prove useful as a way of modelling decision-making behaviour in software agents. In order that software agents are able to perform tasks for users, there needs to be: (i) a method of specifying what these tasks should be; and (ii) a way of specifying to the agent what actions it should take to achieve its task. The first requirement, depending on the environment and required tasks, can be satisfied by either hardcoding some pre-defined behaviour, or allowing the agent to learn, perhaps under supervision.

Within a computational resource allocation system, software agents can work on behalf of users in either resource provision or consumption roles. Utility theory, or more specifically in a computational resource domain, *multi-attribute utility theory*, can be an effective way of allowing agents to make autonomous decisions inline with their owners' preferences and constraints over different resource attributes. Within economic interactions, software agents can be told what actions to choose by being provided with a *utility function*, which the agent can use to make a *preference ordering* over different possible outcomes [183, pp. 107.]. Thus, faced with several choices an agent will go with the one that, according to its utility function, will satisfy it the most. Typically, some assumptions are made about the type of utility model used. Modern Consumer Theory [71, part i.] tells us that human preferences are best described using *ordinal* utility functions, that is, described entirely in terms of rank between alternatives. However, for decision making agents, and the algorithms they employ, it is often preferable to accept the more outdated theory of *cardinal utility* [152], which can, if used with care, accurately model user preferences.

### 2.1.3 Computational resource allocation desiderata

A significant desideratum that concerns the design of resource allocation systems, is that of facilitating *economic efficiency*. Specifically, when dealing with a utilitarian model, it is the *allocative efficiency* of a resource allocation mechanism that is of interest. An allocation is said to be strictly efficient *iff* the

## 2.1. AGENT-BASED COMPUTATIONAL RESOURCE ALLOCATION

total utility of all participants involved is maximised; as a consequence, such an allocation is also *Pareto efficient*. However, within the design of any large-scale, distributed and open system, there will always be practical issues and constraints that must be adhered to whenever possible; there are certainly objectives that must be met when considering the suitability of approaches for allocating distributed computational resources. Unfortunately, these practical objectives are often in conflict with the overarching one of allocating resources as efficiently as possible, and tradeoffs must be made between objectives [136]. Therefore, in reality many resource allocation mechanisms are not strictly allocatively efficient, and the role of a multi-agent system designer is to strive for efficiency while complying with practical system constraints or alternative objectives. When designing a distributed resource allocation mechanism, for example, one might consider the following desiderata:

- *availability*: the allocation mechanism should always be available to agents, not just across locations, but across time—it shouldn't involve periods of inactivity;
- *robustness*: the approach should be *robust to failure*—the entire system should not be reliant on a single point;
- *scalability*: the approach should scale with the number of participants in the system, which in the case of massively distributed utility computing, could be thousands or more;
- *expediency*: users or agents should not be left waiting to receive the outcome of an action—resources should be allocated as quickly as possible; and
- *open*: there should be no barrier to entry, and the approach should not prevent users or their agents from participating.

Current *system-centric* approaches used within grid and cloud computing models for allocating resources fail to meet some of these requirements. In the main, it is unclear how resources can be efficiently allocated within an oligopolistic retail-inspired model. Firstly, it is likely there will be many times when there is, for example, excess supply, but prices won't be adjusted to reflect that. Secondly,



acting in an oligopolistic fashion precludes users from making their computational resources available for provision, further hindering competition. Particularly, with the massive growth of Internet-enabled devices, and thus the continual requirement for access to more computational services and resources, to satisfy a growing user base, means that traditional *system-centric* approaches to controlling and allocating these resources is particularly limiting [63]. In any distributed and open system, where any agent can seek to either provide or consume resources, it is important that agents are able to *compete* for resources, so that those who value them most receive them. As Broberg et al. [20] note, market-based approaches are a possible way of allowing participants to compete over resources, without the need for a global overview of either side of the system required by a system-centric approach.

## 2.2 Market-based Mechanisms for Multi-attribute Resource Allocation

The traditional resource allocation approaches discussed in the previous section all have some fundamental issues, each of which may eventually prove insurmountable. This section considers the domain of *Market-based Control* (MBC) [30], in which market-based mechanisms are utilised to control the allocation of distributed resources, often in complex systems. MBC advocates that, rather than allocating resources according to quantity limits and capacity (which requires an omniscient centralised planner), a system's resources should instead be allocated according to *economic need*, as determined by *price* [68]. Market-based control is founded on the idea that rational self-interested agents will compete over resources, and that they will be allocated to those who place the highest value upon them. Thus, the design of the market-mechanism that governs the resource allocation is fundamentally important for achieving the desired objectives of the designer.

## 2.2. MARKET-BASED MECHANISMS FOR MULTI-ATTRIBUTE RESOURCE ALLOCATION

Within the discipline of economics, the field of *Mechanism Design* concerns itself with the design of market-based mechanisms for resource allocation problems [63]. Mechanism design treats the designing of mechanisms as setting the rules of a game for self-interested agents, such that when followed in a rational way, participants' interactions will lead to designer-desirable outcomes [40]. Mechanism design researchers often have societal objectives in mind when designing market mechanisms; a common goal is the efficient allocation of resources, which is usually defined as the maximisation of the total utility over all agents in the system. By using game-theoretic techniques, the challenge is to design a mechanism that uses the strongest game-theoretic *solution concept* possible [126]. Mechanism designers usually wish to build market mechanisms that satisfy (see [136], for example) the following properties:

- *incentive compatible*: participants should be incentivised to report their true preferences, usually in terms of declaring their true valuation for the good being traded in the market;
- *budget balanced*: if the mechanism rewards participants to reveal their true preferences using money, the net transfer of payments should be zero, i.e., the mechanism does not run at a loss;
- *efficient*: the allocation that the mechanism makes should (in some way) be optimal, e.g., the total utility over all participants should be maximised;
- *individually rational*: participants should be better off (in an expected sense) using the mechanism than not.

An important result often relied upon in mechanism design is the *revelation principle*, which states that any mechanism can be turned into an *incentive-compatible direct-revelation* mechanism [126, 130]. Incentive compatibility is desirable for optimally allocating resources, while a direct-revelation mechanism means that the only available action an agent has is to communicate its preferences; thus, agents can only perform one action, which is to report their preferences truthfully to the mechanisms. In such a case, very strong claims can be made, indeed proved, about the optimality and thus power,

of such a market mechanism. However, there are some considerable problems with the revelation principle. While it states that any mechanism can be turned into an incentive-compatible direct-revelation mechanism, it says nothing about the computational cost of performing that operation [126, p. 36.], such as, for example, polling every agent in a system for their preference type [137]. Other strong assumptions are often also made, such as implicitly trusting the market mechanism, and that agents will always act rationally. Thus, the mechanism design desiderata listed above, and the general approach and assumptions, are in conflict with the desirable properties of a computational resource allocation mechanism listed in Section 2.1.3. Some new approaches have been made to improve the practical aspects of mechanism design, e.g., *algorithmic mechanism design* [115] only considers mechanisms that are computationally practical, and *trust-based mechanism design* [40] considers mechanisms where traders may not fully trust each other, often because of conflicting design objectives, the design of *appropriate* mechanisms for the problem at hand is usually non-trivial [63] and complex, and theoretical approaches are often not practical.

### 2.2.1 Centralised approaches

A common mechanism for determining where resources should be allocated is to hold an *auction*. The most common type of auction, the *English Auction*, is often found in auction houses dealing with art or antiques. In such an auction, bidders shout out monotonically increasing bids until no-one wishes to improve upon the last price submitted. In the simplest settings auctions are a good method for allocating resources to those who value them the most, because the auction participants are often able to get an overview of the market and the interest in item being auctioned. *Multi-attribute auctions* [14, 11, 13, 26, 41] are auctions where rather than submitting single prices, as in English Auctions, bidders are required to submit a *bundle* of attributes, describing a range of different outcomes they would be happy with, and what they would be prepared to exchange for each

## 2.2. MARKET-BASED MECHANISMS FOR MULTI-ATTRIBUTE RESOURCE ALLOCATION

outcome. Typically, multi-attribute auctions are single-sided, and often, as Bichler et al. [14] note, designed in terms of facilitating procurement within complex resource markets; an example might be a government procuring goods or services to find the cheapest supplier that satisfies their requirements. Multi-attribute bids are often evaluated by the auctioneer, using a scoring-rule or utility function, which allows it to compare bids orthogonally. How these rules are designed is an active area of research [26, 41]. The fact that typically multi-attribute auctions only allocate single-units within each auction, means they can be prohibitive for allocating large volumes of resources. While multi-unit versions have however been considered, some of the advantageous properties of the single-unit versions, including the efficiency of allocations, is lost [14].

*Combinatorial Auctions* [114] are multi-unit auctions that attempt to overcome some of the limitations of traditional multi-attribute auctions. A combinatorial auction considers the allocation not of individual goods with multiple attributes, but entire bundles of different goods. Examples might include for example, the various aspects of a package holiday: flights; connections; and hotel. Importantly, goods are said to be combinatorial only when the value of the bundle is greater than the total of each item's individual value [12]. While combinatorial auctions are able to efficiently allocate resources, the *winner determination problem*, that is, the optimisation problem needed to be solved to optimally allocate resources, is a reduction of a graph clique problem, and thus  $\mathcal{NP}$ -hard [148]. While the problem is  $\mathcal{NP}$ -hard, some attempts have been made to provide more computationally reasonable estimation algorithms for calculating optimal allocations, particularly in terms of iterative mechanism that can find sub-optimal allocations in polynomial time [125, 126]. Similar approaches have been proposed and evaluated in multi-attribute auction formats [163, 13].

## 2.2.2 Decentralised approaches

The centralised auction-based mechanisms discussed thus far, while often resulting in allocatively efficient outcomes, rely on considerable amounts of central control or *global views*, which is at odds with the general aims of market-based systems—to exhibit the decentralised, robust nature of human economies [35]. Several approaches have been proposed for the design of agents, and in general mechanisms, for the decentralised allocation of resources. In terms of being applicable to computational resource allocation, there are two main approaches: bargaining over resources using negotiation protocols, or broadcasting ‘take-it-or-leave-it’ posted offers across retail markets.

Lewis et al. [92] take a decentralised retail-inspired approach to the allocation of computational resources, defining *evolutionary market agents*—resource sellers that use simple evolutionary algorithms to learn appropriate prices for selling resources. Within their model, no centralised node or coordinator is required to manage the resource allocation process. Rather, it is assumed that a decentralised population of resource consumers and providers are able to interact with each other and post offers publicly to the rest of the entire system. While Lewis et al. focussed on single-attribute resources, the approach has also been generalised to multi-attribute cases [93]. While Lewis et al.’s approach satisfies a number of desirable properties, such as robustness through decentralisation, it has a number of drawbacks. It assumes that sellers have an unlimited amount of resources, and it is unclear how efficient allocations would be in scenarios where sellers were resource constrained, or indeed, how sellers would ensure their prices were visible to all buyers in the system.

Bargaining agents can use a more complex formal framework for negotiations. Some heuristic approaches to bargaining, such as Barbuceanu and Lo [6]’s, utilise models that can order preferences over multi-attribute resources. Bilateral negotiations progress with each agent considering an offer according to

## 2.2. MARKET-BASED MECHANISMS FOR MULTI-ATTRIBUTE RESOURCE ALLOCATION

their valuation model and returning a (generally concessive) counter offer, or rejecting the deal entirely. Heuristic bargaining approaches are not capable of considering externalities, or indeed communicating outside of the bounds of the proposal space [78], which can lead to inefficient negotiations and an inability to communicate other important information. Argumentation approaches [128, 78] attempt to remove some of these limitations by allowing agents to communicate, for example, supporting arguments as to why their proposal should be accepted, or to notify the counterparty of particular constraints that can't be broken.

As with decentralised retail-inspired approaches, it is unclear how well bargaining approaches result in efficient allocations across systems of distributed agents. Work on CATNETS [53, 54] has attempted to answer these types of question. Eymann et al. [53, 54] consider fully decentralised resource allocation mechanisms for computational grids that rely on networks of different software agents acting as providers or coordinators. Each agent uses negotiation techniques to make a trading decision, and an underlying decentralised peer-to-peer infrastructure allows agents to communicate prices and offers. While this approach is reasonable for small cases, as the number of participants scales to several hundred, results in [54] suggest the fully decentralised nature significantly affects convergence on an efficient price equilibrium.

### 2.2.3 Problems with existing approaches

In this section a number of centralised and decentralised market-mechanisms have been reviewed from the perspective of multi-attribute computational resource allocation in large-scale systems. While each approach has a number of advantages, both approaches have significant issues or limitations, which do not sit well with the desiderata listed in Section 2.1.3. The significant advantage of centralised auction-based approaches is that in many cases they are able to achieve two things: (i) elicit the true preferences of bidders; and (ii) use this information to calculate the most efficient allocation, usually by solving an

optimisation problem. However, these outcomes are reached at a significant cost:

- *non-distributable*: it is unclear how multi-attribute and combinatorial auctions could be distributed across many locations in a large system, while maintaining their primary advantage of allocating resources efficiently;
- *one-sided*: the centralised mechanisms considered thus far only install competition in one side of a market, giving a potentially unfair advantage the side running the auction [151];
- *non-interruptible*: there could be a significant gap between the commencement of a centralised auction, and the resulting allocation, during which time the environment or preferences of the agents may change considerably;
- *computationally prohibitive*: eliciting the true preferences of agents, and then solving the resulting allocation problem is generally  $\mathcal{NP}$ -hard, and near realtime resource allocations with large systems of agents seems impossible with current computational hardware.

Some research has been undertaken to generalise multi-attribute and combinatorial approaches to two-sided exchange markets [127, 151], but there are still many issues remaining in terms of computational cost and the non-interruptible nature of the mechanisms. Cliff and Bruten [35] were one of the first to suggest that a centralised approach to resource allocation, whether via market mechanisms or not, opposes the decentralised, robust nature of real-world economic markets; a call was made for focussing on developing agents that are capable bargaining behaviours, that is, to *distribute* the intelligence of the mechanism across the system. In real-world free-market economies, competition between market participants drives the allocation process. However, the fully decentralised approaches studied in Section 2.2.2 hinder this in a number of ways:

- *hidden-prices*: two significant issues hinder economic competition in fully decentralised systems—either transaction prices are private and not available publicly, or prices are unevenly distributed across a decentralised network;
- *illiquidity*: in large-scale systems, where market participants have heterogeneous preferences and constraints, it can be hard to find suitable trading partners;

### 2.3. DOUBLE AUCTIONS

- *barrier to entry*: agents capable of multi-attribute negotiating need to have sophisticated levels of cognitive reasoning.

Price discovery is essential to allow competition over resources and ensure that those who value them most, receive them. In the CATNET approaches [3, 54], however, prices have to be communicated in an ad-hoc way around the system, potentially putting agents on the periphery at a disadvantage. Further, as Bichler [12] notes: in bilateral bargaining situations, one-to-one negotiations determine the price and conditions of any deal. This suggests that outcomes are economically indeterminate, because agents with higher cognitive capabilities will determine the conditions and prices of deals.

When Cliff and Bruten [35] highlighted the importance of distributing the intelligence of market mechanisms by endowing market participants with bargaining behaviours, they emphasised that to allow economic competition to occur within a market, bargaining agents need to be able to consider other recent trade prices when forming their own. If there is a mechanism to make price information to available to *all* market participants, bargaining behaviours do not need to be considerably complex for efficient outcomes to be achieved. Cliff and Bruten demonstrated this by showing that a population of minimally intelligent traders [33] can arrive at economically efficient allocations without the need for any omniscient central mechanism controlling allocations. This mechanism, the double auction, forms the core of the market-based system proposed within this thesis, and is discussed in the next section.

## 2.3 Double Auctions

This section introduces the *Double Auction*—a family of *two-sided* auction mechanisms where multiple potential buyers and sellers submit offers, seeking to engage in purchase transactions over some good. As a market-mechanism for allocating computational resources, whose providers and potential consumers are



distributed over space and time, a double auction has some nice properties:

- *institutional*: as a centralised auction mechanism, it provides a single location for participants to trade;
- *price discovery*: participants have access to the current market price for the resource they are trading;
- *two-sided*: the double auction supports multiple buyers and sellers simultaneously bidding in an attempt to transact.

While a centralised institutional mechanism may appear to conflict with some of the desiderata in Section 2.1.3, e.g., by being a weak-point of failure, in reality, multiple double auction mechanisms are easily distributed across a system, and participants can migrate between them at will [23]. Further, double auction mechanisms do not *require* knowledge of the whole system, and merely act as a point for traders to compete over resources, rather than making any dictatorial allocation decisions. Because they are two-sided auctions, both buyers *and* sellers can compete over resources, ensuring no side of the market has an unfair advantage.

### 2.3.1 Double auction basics

The term ‘double auction’ is rather misleading. While many auction mechanisms are considered double auctions, in reality double auction is an umbrella term for many two-sided auction types, each with different rules but sharing some characteristics. Double auction variations are used by most of the stock and commodity exchanges around the world, but generally each has differing rules. In a double auction, traders *simultaneously* submit prices—referred to as *shouts*—to the market [58]. Buyers’ shouts are known as *bids*, and indicate that they are prepared to purchase at a price not exceeding their specified offer price. Sellers’ shouts are referred to as *asks*; an ask is an indication that the seller is prepared to sell at a price not less than their specified offer price. Bids and asks can be *matched* when their prices crossover, that is, when the bid price is at least that of

### 2.3. DOUBLE AUCTIONS

the ask price. Once a bid and ask are matched, a *transaction* is formed between the buyer and seller, and they exchange good for cash. One common type of double auction is the *clearing house* auction, or *call market* [49]. A clearing house auction is *periodic*, that is, like the classic English auction there is a period of bidding, and then a period of allocation. Once bidding is over, the auctioneer assesses all offers and determines which traders will be matched, and at what price. It is common in call markets for all matched traders to transact at the *same* price, which is typically known as the *clearing* or *market* price, because it is the price at which, given all of the offers, the most transactions can be executed. An illustrative example of how the market is cleared is given in Figure 2.1. Clearing

<i>bids</i>	<i>asks</i>
14	6
14	7
13	9
12	9
10	10
9	13
9	14

Figure 2.1: Each number represents the price of an offer shouted into the market. Once the submission period is over, the auctioneer determines the clearing (or market) price. In this case the market price is 10. All possible trades, i.e., those on or above the clearing price will take place with a transaction price of 10. Thus, the price discovery is performed by the market mechanism rather than the traders. For example, one bidder has over-bid and offered a price of 14, but they will only pay the market price.

house auctions are useful for trading items that don't have continually high amount of interest, because they provide an extended period of time to collect potential offers before allocating resources. Further, traders do not have to worry about over-bidding, because the price discovery process is done by the auctioneer. Clearing house auctions do a good job of *discovering* market prices, by spending time gathering information about trader preferences, in the form of collecting offers, resulting in more efficient allocations. However, their periodic nature does not sit well with the desideratum that resources should be allocated

quickly, e.g., it may be impractical for a software agent to wait for the next auction iteration. Further, the periodic nature means that clearing house markets can take longer to react to *exogenous* environmental influences acting on the system, such as sudden shifts in supply or demand. An always-on *continuous* double auction mechanism, where market prices are determined, and resources allocated instantly, is more appropriate.

### 2.3.2 Continuous double auctions

Unlike the clearing house auction, an auctioneer running a continuous double auction (CDA) clears the market as soon as two offers match. In a CDA market traders always have an indication of the current market *spread*, which typically displays the currently unmatched highest bid and lowest ask. Thus, traders using the CDA market mechanism always have access to the current market price (often called the market quote), which is the price they must pay that *instant* to either buy or sell a resource. CDA mechanisms are the double auction variants that are most likely to be found running in financial institutions around the world, particularly as a way of allocating heavily traded assets. It is common to refer to the entities running CDA auctions as either market institutions, or market-exchanges; this thesis uses the second term. Given that CDAs allocate resources in a continuous, reactive way—as soon as two offers cross in the market, and all at potentially different prices—the resulting allocations are often very efficient. Expectedly, CDAs have therefore received a large amount of attention from within the Economics, and increasingly also the Computer Science research communities.

#### Reaching competitive equilibrium with minimally intelligent traders

*Competitive Equilibrium* is a term used to describe the concept of equilibrium in a two-sided exchange environment (where prices can be dictated by both supply and demand). Equilibrium usually implies stability; if a market reaches

### 2.3. DOUBLE AUCTIONS

competitive equilibrium, trades all tend to take place at a certain price, known as the *competitive equilibrium price* (often denoted  $P^*$ ). Further, competitive equilibrium results in allocations that are allocatively efficient, in terms of maximising total trader utility, which is a desirable objective for a computational resource allocation system. To understand how competitive equilibrium is arrived

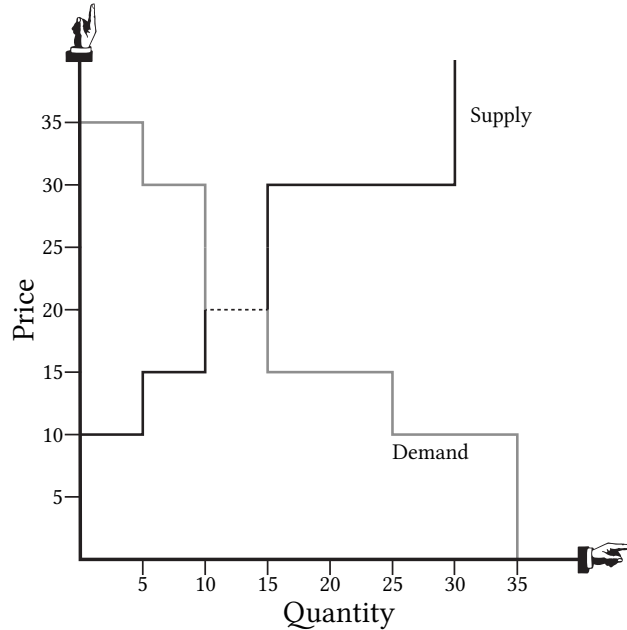


Figure 2.2: Example *supply* and *demand* curves for a resource market. Supply curves always slope upwards (the higher the price of a resource, the greater the number of traders willing to supply the resource). Demand curves almost always slope downwards (the lower the price of the resource, the greater the number of trader wanting to purchase it). Given supply and demand schedules, the curves can be built by iterating through all prices and recording the quantity of traders that would be willing to trade at that price. Assuming traders can only trader a single unit, at a price of 10, for example, five sellers would be willing to trader, but at that price 35 buyers are eager to buy, resulting in an *excess demand* of 30, which is inefficient in terms of maximising total utility across all traders. Likewise, at a price of 10 there is an excess in supply of  $30 - 10 = 20$ . However, at the equilibrium price  $P^* = 20$ , the quantity willing to be supplied is *equal* to the quantity demanded, thus the market is at competitive equilibrium. In this the equilibrium quantity is a range  $Q^* \in [10-15]$ , but the quantity exchanged will tend towards the maximum limit [157, p. 114.].

at, and to further support the argument for the applicability of using double auction mechanisms for allocating computational resources, example *supply and demand curves* are shown in Figure 2.2. These curves are built from the private

valuations of a group of 35 traders who wish to consume or provide an imaginary resource. An allocation of this resource is efficient when supply and demand are equal, i.e., the 15 traders who can, trade at a price of 20. However, the CDA mechanism cannot enforce this, because it does not know traders' valuations, and it allocates individual resources constantly, without building a picture of the supply and demand schedules. Yet, equilibrium outcomes *are* achieved using this mechanism, even in markets with relatively few traders [157, 67]. This outcome is down to the price discovery process, specifically that traders always know what they need to pay, *at that present time*, to buy or sell a resource.

The primary feature is the double auction structure: in order to realize any gains from exchange, a trader must either seize the market price, or accept the market price of another. This necessity both limits each agent's influence on prices (via Bertrand competition) and also conveys high quality information to other agents.

Friedman[57, p. 71.]

From a Computer Science perspective, designing agent-based traders that are capable of behaving in this way is of paramount importance for applications such as the one this thesis is interested in.

In seminal work, Cliff and Bruten [33], building upon previous, but ultimately incorrect conclusions [66], developed the *Zero-intelligence Plus* (ZIP) trading agent, which, using simple machine learning techniques, is able to reach competitive market equilibrium under a range of market conditions. Further, it is a very simple algorithm which is computationally cheap to run.

### 2.3.3 Multi-attribute double auction approaches

Up to this point, double auctions, and particularly the continuous double auction, have been discussed with respect to single-attribute resources. The double-auction is, in its most common configuration, designed only to allow traders to indirectly negotiate over price. Therefore, all resources or goods that are supplied across a typical double auction market are *commodities*, that is, each

### 2.3. DOUBLE AUCTIONS

item allocated is qualitatively indifferent to any other. Within the literature, a small number of multi-attribute double auction mechanisms have been proposed, which will now be reviewed. Fink et al. [56, 55] have built formal models for trading multi-attribute goods using a CDA mechanism. As an example application, they consider a market for trading new and used cars with four non-price attributes. Each buyer and seller is assumed to be able to specify quite complicated constraints and preferences to the auction, e.g., “I’ll pay \$200 more if the car is red, but no more than \$10,000 if it is black.” As such, traders submit offers not as a single price, but as a bundle containing (amongst other things) a set of car types of interest, and real-valued functions describing preferences and constraints over those types. There are a number of reasons why Fink et al.’s model is not suitable for the application considered in this thesis. Firstly, in a single-attribute CDA mechanism, when an offer is submitted, it only has to be compared to the highest (lowest) unmatched bid (ask), which is a cheap operation. In Fink et al.’s mechanism, each offer submitted, being of a multi-attribute nature, must be compared to *many* unmatched offers; indeed, the matching operation is equivalent to a single-sided multi-attribute auction’s mechanism. Secondly, Fink et al. differentiate between *indexable* orders (those that are only interested in a single type of car), and *non-indexable* orders (as the example above, where a trader is interested in a range of different types of car). In an effort to reduce computational cost, potentially more efficient allocations are sacrificed by only matching non-indexable to indexable orders, reducing the difficulty of the matching problem. Both Engel et al. [51] and Schnizler et al. [151] do consider the more complicated case of optimally matching a two-sided market where offers are submitted with multiple attributes. As well as being considerably harder than in the CDA-based mechanism used in [56, 55], the computational complexity of the resulting optimisation problems in [51] and [151] is considerably worse than the single-sided mechanisms discussed in Section 2.2.1. In both [51] and [151], integer programming solutions are developed, however,

based upon reported results, they are only feasible for real-time allocations of computational resources between low numbers of traders, e.g. less than 100.

### 2.3.4 Commodifying multi-attribute resources

In practice, the continuous nature of the CDA mechanism precludes it from optimally allocating multi-attribute resources with any kind of expedience, when the mechanism accepts multi-attribute offers, i.e., offers specifying not just price, but also constraints and preferences over other attributes. The rest of this section motivates this thesis's proposal that multi-attribute computational resources can be allocated via competing CDA marketplaces. It discusses how the financial world deals with allocating hundreds of thousands of multi-attribute goods every day, how the techniques used to achieve this have begun to feed into utility computing models, and concludes with the proposal for multi-attribute resource allocation via competing marketplaces.

Unlike *cash instruments*, such as company stock, which have an equivalent value to all market participants, more complex instruments, e.g., those that are *derived* from aspects of other instruments, can have different values to different participants, due to their multi-attribute nature. An *Option* is an example of a multi-attribute financial derivative. An option contract between two parties stipulates the buyer of the contract is entitled to, at some future point specified by the contract, either buy or sell some underlying asset, to or from the seller of the contract. They have a long past<sup>2</sup>, and until 1973 they were traded *over the counter* (OTC). OTC transactions involve direct or indirect (via a broker) negotiation over the attributes of the contract being exchanged. Given the distributed nature of the global economy, and contract heterogeneity due to non-standardised attributes, it was often hard to find parties to trade with, and exchange would take considerable time.

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<sup>2</sup>There are references to option-like contracts between people in the Bible [123, p. 1. ], for example, and certainly a well-recorded instance of option contract trading for Tulips, in seventeenth century Holland.

### 2.3. DOUBLE AUCTIONS

The solution to this was (along with the standardisation of the various contract attributes) the opening of the Chicago Board Options Exchange [28] (CBOE) in 1973; with its opening began a new era of *exchange-traded* options. Exchange-traded options are, as the name suggests, traded over an exchange, usually either a call market or a CDA market. The significant difference between exchange-traded and OTC traded options, is that there is no negotiation over non-price attributes in the exchange-traded case, that is, all non-price attributes are *fixed* to some specific values. Each option contract variation is traded within its own *market*, and thus there are separate auctions for each variant. To deal with the different preferences and constraints that traders have over contract attributes, option exchanges run *multiple* markets, giving traders the ability to trade the option contract variant that best meets their preferences and constraints. One fundamental challenge that an exchange owner faces is deciding how many different types of markets to run, and what type of contract variant should be traded within each market. To improve the liquidity within markets, exchanges offer a subset of markets that have a large interest from traders. An

Type	Underlying	Strike Price	Expiration	Current Bid	Current ask
CALL	IBM	145	19/01/11	6.20	6.30
CALL	IBM	150	19/01/11	2.96	3.00
CALL	IBM	155	19/01/11	1.05	1.10
CALL	IBM	160	19/01/11	0.30	0.32
PUT	IBM	145	19/01/11	1.61	1.62
PUT	IBM	150	19/01/11	3.45	3.55
PUT	IBM	155	19/01/11	6.65	6.75
PUT	IBM	160	19/01/11	10.90	11.00

Table 2.1: A fictional example of eight different option contract variations for the same underlying asset. Each row in the table specifies a separate market for contract types with the attributes specified in columns 1–4. These attributes include the underlying asset, whether purchaser is given the option is to buy or sell the underlying (Type), at what price (Strike Price), and on what date (Expiration). Each market is a separate auction, and the current *market quote* for each type of option contract is shown in columns 5 (bid) and 6 (ask). Traders can choose to join any of the separate markets and shout offers, according to whichever market they are interested in.



illustrative example is shown in Table 2.1, which lists some fictional *markets* for exchange-traded IBM options. Each contract has four non-price attributes, which traditionally would be negotiated over. Rather, these attributes are fixed at specific levels and markets for a range of different contract variations are provided; each market has a current *market quote*—the current price to buy and sell instantiations of those contracts.

The standardisation of complex multi-attribute financial derivatives has allowed for the emergence of commodified multi-attribute contract markets running across distributed exchanges, lowering cognitive requirements of automated trading strategies. Rather than having to design agents that can negotiate over complex attributes with brokers, simple CDA trading strategies such as ZIP can be utilised. Recently, similar exchange-based approaches have begun to emerge within the utility computing model. Cloud providers such as Amazon have recently begun to introduce a market-based approach<sup>3</sup>, by providing call markets for allocating different multi-attribute computational resources. Consumers choose the market that best meets their requirements and submit bids for access to instances of the specified market resource. Knowing its own supply schedule, based upon its current excess capacity, Amazon essentially acts as multiple sellers on the sell-side of each market, clearing the markets at prices that balance supply and demand. A selection of these resource types is shown in Table 2.2; each of the resource types has a different market price, dependent on the available supply and demand. Because Amazon is aware of its hardware capacity, it has explicit knowledge of the entire supply schedule. Based upon that, human experts can optimise the selection of attribute-levels for each of the resource markets, to best match the demand of users, and optimise revenues.

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<sup>3</sup><http://aws.amazon.com/ec2/spot-instances/>

### 2.3. DOUBLE AUCTIONS

Compute Units (CPU)	Memory	Storage	I/O Performance	Architecture
1	1.7 GB	160 GB	Moderate	32-bit
4	7.5 GB	850 GB	High	64-bit
8	15 GB	1,690 GB	High	64-bit
6.5	17.1 GB	420 GB	Moderate	64-bit
13	34.2 GB	850 GB	High	64-bit
26	68.4 GB	1,690 GB	High	64-bit

Table 2.2: Six different *Amazon EC2 Instance Types*. Each row represents a different type of computational resource offered on-demand by Amazon web services. As you can see, each instance type has different attribute values, which will be preferable to different types of consumers. Amazon provides a separate exchange market for each resource type, and consumers submit bids for purchasing instances of the described resources. Amazon decides which resource markets to offer based upon its explicit knowledge of the supply schedule, i.e., it knows how much excess capacity is in its system, and the hardware constraints of its infrastructure.

#### Summary

While Amazon is an example of where market-based approaches are being considered for complex computational resource allocation, in their case they have full knowledge of one side of the market. Thus, they can optimally specify what resource markets should exist, e.g., those in Table 2.2, based upon knowledge of their resources. However, the distributed resource providers and consumers considered within this thesis are distributed across space and time, with different preferences and constraints, resulting in global supply and demand schedules being unavailable to any single entity.

One approach to computational resource allocation not yet considered in the literature, is that resource markets could be run by multiple competing marketplaces, with the aim that each marketplace automatically identifies a *market niche* that satisfies a *market segment*. Market segmentation is an economics and marketing concept that describes how a population of market participants is segmented into different groups [89, p. 73]. These market segments are often defined by the preferences and constraints of consumer and providers, which cause them to demand similar or identical goods. In that respect, marketplaces attempting to satisfy market segments by providing a market for a

certain resource types face the same problem as financial derivative exchanges: identifying and satisfying market segments within a complex environment containing many participants with different preferences and constraints over attributes. How the market-exchange agents running these markets autonomously identify and satisfy market segments, to attract consumer and providers to their market, is a research question considered in detail in Chapter 5. It is hypothesised, however, that their self-interested nature, and thus the competition over traders, will encourage all market niches within an environment to be sought out and satisfied.

Recently, a small body of related research has appeared, looking at answering research questions involving satisfaction of market segments via multiple competing marketplaces. Cai et al. [23], for example, have empirically investigated the emergence of market segmentation between competing market-exchanges in a less complex single-attribute resource domain. Using an empirical agent-based approach, they conclude that the competitive nature of traders will result in them naturally migrating to their preferred market, thereby creating separate markets for each segment of the trader population. Both agent-based approaches to the design of marketplaces, and simulation frameworks for analysing competition between them, are a major part of the research carried out in this thesis, and form the topic of the next section.

## 2.4 Competition Between Marketplaces

This section focusses on the computer science literature that studies competition between marketplaces. Particular attention is given to the various empirical approaches that have been suggested as frameworks for the design and analysis of double auction market-mechanisms both in isolation [31, 135, 136], and in competition in complex environments [117, 24]. While these approaches are certainly helpful for analysing the performance of marketplaces competing in

## 2.4. COMPETITION BETWEEN MARKETPLACES

dynamic environments, there has been less attention given to methods for analysing the robustness and generalisation of market-mechanisms; this is discussed in more detail at the end of the section.

In a global economy, stock exchanges compete against each other for trading business, and, increasingly, against new online markets not tied to traditional physical exchanges. In such a competitive environment, the precise rules adopted by a marketplace may have important consequences: in attracting (or not) traders to their exchange; in favouring (or not) certain trading strategies; and in facilitating (or not) the matching of shouts and the execution (matching) of trades in their market. As such, marketplaces often use a variety of different rules<sup>4</sup> in an attempt to get a competitive edge. Thus, a detailed understanding of the different potential rules for double auction markets and their impacts is important, since a good understanding of the market rules used certainly helps in the design of improved rules and mechanisms, and may offer clues as to how we might eventually *automate* the design of entire market mechanisms.

### 2.4.1 Approaches to double auction marketplace design

Unfortunately, double auctions are typically poorly understood from a theoretical perspective, in comparison to their single-sided counterparts [12, 130]. As both Parsons et al. [130] and Phelps [137] note, while it has been shown that single-sided mechanisms with one seller can be budget balanced, efficient and incentive compatible, due to Myerson and Satterthwaite's [111] impossibility result, no exchange-based (two-sided) mechanism can achieve all three objectives. Further, the two-sided nature of the auction means game-theoretic approaches have only been useful for very small instances, because of the huge state-space explosion when considering larger numbers of participants and all their possible actions. Thus, given the double auction's current mathematical intractability for

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<sup>4</sup>For example, the New York Stock Exchange [113] use a rule known as the the *NYSE rule* [48, p. 84], which specifies traders must continually *better the market* every time they shout an offer

larger instances, more attention has been given to *empirical analysis*, particularly through the use of simulation and agent-based modelling.

Wurman et al. [186] perhaps seeded the empirical approach to marketplace design, when they set about parametrically specifying common auction characteristics—rule variations—that covered a large variety of different auction formats. Based on the approach of Wurman et al., Niu et al. [116] developed a rule framework more specific to double auction mechanisms, which helps to tackle design and analysis aspects of the mechanism by defining a set of *policies* that constitute a double auction mechanism, and could be used as parts of agent-based double auction implementations:

- *Matching* policies specify which of the submitted traders' offers should be paired to form a transaction between the two agents;
- *Quoting* policies specify the current market *bid price* and *ask price*. These two prices are used by traders to help them determine what offer price they should submit in the future.
- *Shout Accepting* policies either accept or reject a trader's submitted shouted offer price;
- *Clearing* policies specify under what conditions the market is cleared, i.e., all transactions between matched offers are executed.
- *Pricing* policies determine, given matched bid and ask offers, at what price the transaction should take place;
- *Charging* policies specify to traders what types of charges they are subjected to when, for example, joining the exchange, placing a shout in the market, or successfully transacting.

Based on these broad but well defined policy areas, researchers have used a variety of techniques to explore the design space of double auctions. Within the realm of designing and analysing single market mechanisms in isolation, with the typical objective of designing more efficient mechanisms, research has focussed on automating the search across the design space. Cliff [31, 32] applies an evolutionary approach to coevolve both autonomous ZIP trading agents [34] and a CDA market-mechanism. Specifically, Cliff uses a *genetic algorithm* to evolve single vectors of real-value parameters describing properties of both the trading

## 2.4. COMPETITION BETWEEN MARKETPLACES

agent and market-mechanism behaviours. The evolutionary process results in the finding of several novel market-mechanism that outperform well-known variants. Phelps et al. [136] have recently introduced the *Evolutionary Mechanism Design* approach, wherein the problem of designing auction mechanisms can be treated as an economic engineering problem [147] that needs to be iteratively solved, rather than formally proved. To that end, Evolutionary Mechanism Design makes use of empirical game theory techniques [135], as well as evolutionary algorithms—particularly Genetic Programming techniques—to explore the design space of double auction mechanisms [134].

### 2.4.2 Analysing competing marketplaces

Approaches such as [31, 136] have ostensibly been used to design marketplaces existing in isolation, that is, in environments where there is no competition between market mechanisms. In order to promote research into automated mechanism design, and specifically to act as a basis for better understanding how, in a competitive environment, the rules adopted by marketplaces impact their performance, a new research tournament was launched in 2007: *the Trading Agent Competition Market Design (or CAT) Tournament* [24].

The CAT Tournament comprises a series of artificial parallel markets, designed to mirror the competition between global stock markets. These parallel markets, called *specialists*, are created by entrants to the Tournament, and they compete with one another to attract and retain traders, who are potential buyers and sellers of some abstract commodity. In the CAT Tournament, traders are software agents created and operated by Tournament organisers and the tournament entrants have to provide trading venues, in the form of specialists—a specific name for a type of market-exchange. Each specialist agent runs a double auction mechanism, whose rules are set within the six broad policy areas defined by Niu et al. [116] (referred to on Page 40). Along with different potential trader types in the environment, the multi-dimensionality of the specialists’

performance metric creates challenges for the optimal design of specialists, since these criteria may conflict. The rich environment created by, not only many traders competing with each other, but also many market mechanisms competing to attract traders, creates a potentially excellent test-bed for evaluating the effects of different market mechanism rules.

The JCAT [77] software, which is used to help run the tournaments, is available freely and allows users to quickly create various environmental conditions to evaluate specialist agents, and the effects of competition on their performance. As such, there have been several researchers making use of the platform to carry out either specific analyses of the various CAT tournaments [132, 116, 117, 174, 119], or to analyse competitive marketplaces in other contexts [158, 159, 154]. Because the entrants to the CAT tournaments do not have to submit source code, the tournament has created interesting new research avenues, such as how to *reverse engineer* market mechanism rules, based only on observing interactions between market mechanisms and traders [117] in competition. The CAT tournaments have also highlighted aspects of marketplace design that are not often considered when designing isolated mechanisms. Petric et al. [132] found that their 2007 CAT tournament specialist: CrocodileAgent, won the initial qualification stage of the tournament, but only managed 3rd place in the final because other competitors noticed the strategy and mimicked it within the final stages. In terms of research undertaken outside of the CAT tournament, but within the context of competing marketplaces, Shi et al. [154] use an evolutionary game theoretic approach to analyse the migration of traders in a two-market situation, where the exchanges charge registration fees. Based on their analysis they find that traders will almost always migrate to a single market, but that sometimes that market might be the one charging the higher fees, suggesting that some interesting and complex dynamics affect the relationship between market rules and performance. Similarly, Sohn et al. [159] also consider competition between two exchanges, and how the fee structures affect market

## 2.4. COMPETITION BETWEEN MARKETPLACES

share. Sohn et al. assume that for market-selection, traders have a game-theoretic behaviour model, and will thus make rational market-selection decisions.

Running simulations, they find that as an exchange increases its entrance fees, though *extra-marginal*<sup>5</sup> traders are driven away immediately, there are still several Nash equilibria<sup>6</sup> where *intra-marginal*<sup>7</sup> traders still join the exchange.

### 2.4.3 Generalisation and robustness issues

Using simulation tools such as JCAT can be an effective way of answering research questions involving competition between marketplaces, as well as being an excellent way to empirically test and analyse market mechanism performance in general. Further, these types of analysis are examples of how rich agent-based simulations of competing marketplaces can often reveal results that would otherwise be unlikely to be found by studying mechanisms in isolation.

However, it may well be the case that the performance of a market mechanism (or indeed a buyer/seller agent) may depend heavily on the *environmental context* it is situated in. For example, given the CAT game structure, it is easy to see that some specialists may perform better with traders of a particular type, and/or against competing specialists using particular policies. Niu et al. [116], for example, have shown that some of the well-performing 2007 CAT specialists have weaknesses in other situations, and therefore specialists may be considered *brittle* (or obversely, *robust*), if their performance greatly depends (or does not) on the competitive and trader contexts of the environment. Petric et al. [132] note, for example, that from their investigations, results of the CAT tournament are very sensitive to the initial distribution of traders (environmental context) between marketplaces. Because the actual CAT

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<sup>5</sup>Extra-marginal traders are those that, at market equilibrium, bid lower or ask higher than the competitive price, resulting in them being unable to trade.

<sup>6</sup>A Nash equilibrium is a game-theoretic solution concept in which no player wishes to unilaterally change their own strategy, and all players know the equilibrium strategies of all the other players.

<sup>7</sup>Intra-marginal traders are the group of traders that successfully trade at the market equilibrium.



Tournaments are only conducted over a limited number of games (typically, three), the performance of a specialist in the Tournament is not necessarily a good guide to that specialist's *general* ability, i.e., with other trader mixes, or in competition against different specialists.

Thus, there is a need to develop techniques or methodologies for measuring the *general* performance of market mechanisms across a variety of environmental contexts that a mechanism would be expected to operate in. This thesis offers solutions for that need, and uses the contributed techniques to help design and analyse market mechanisms. Away from the CAT tournaments, other examples are available that highlight the potential brittleness of trading strategies also. Sohn et al. [158], for example, report that ZIP traders [34] don't perform well in CDA markets with biased pricing rules. LeBaron [91, pp. 37–38] note that the settings of parameters of economic software agents often affects their performance; this thesis argues that it is also not clear what effect a new *environment* will have on an agent, whose parameter settings were previously successful in others.

In summary, it is very important when designing market mechanisms that attention is given to measuring as well as possible the general performance across environments that the mechanism can expect be in; currently, however, there are gaps in the literature regarding how this can be done for market mechanisms in complex settings.

## 2.5 Trust and Reputation Issues in Open Electronic Markets

Any multi-agent system relies on software agents interacting with others to achieve designated tasks. When the multi-agent system is open, dynamic, and unpredictable, however, it is essential that agents are able to adapt to changes in the environment, and learn which agents to interact with [168]. Given that

## 2.5. TRUST AND REPUTATION ISSUES IN OPEN ELECTRONIC MARKETS

trading partners are unlikely to repeatedly interact, there is little fear of non-normative behaviour being punished, and it is possible that outcomes between self-interested agents could be unfavourable [37, p. 31]. Further, within a large market-based environment, the fact that agents are mostly unfamiliar with each other can lead to sub-optimal trading decisions and potentially reduce the efficiency of allocations.

In economics, the study of *information asymmetry* concerns itself with dealing with economic interactions between agents where one agent has better knowledge of the underlying details of the exchange. In general, there are two types of information asymmetry: *moral hazard* and *adverse selection*. *Moral hazard* occurs when one party decides to not support their part of a contractual agreement, and instead exploits the other party by, for example, not paying for a service provided, or not providing a service paid for [27]. It is a special case of information asymmetry, because rather than one agent having more information about the subject of the exchange, it has more information about its own future actions. *Adverse selection* is a slightly more complex form of information asymmetry; it can have a very detrimental affect on market performance [74]. Adverse selection was first explained by Akerlof [1], and occurs as follows. Given a market containing variable quality products, but where buyers are unable to perceive these quality differences before purchase, buyers will rationally assume all products are of average quality, lowering mean prices. This then repels sellers of high quality products, who cannot get high enough prices. The average quality of products in the market is reduced, and once buyers learn this, average market prices are also lowered. In the end, *market failure* occurs, and only the lowest quality products are traded. In terms of *double auction* electronic markets, information asymmetry can present itself in the following ways:

- *adverse selection* may present itself by:
  - sellers altering the quality or attribute-levels of resources, such that they differ from those expected by buyers within the market;

- in order to reduce the costs of production and increase their profits, or market-exchanges may not provide the service expected of traders;
- *moral hazard* could be exerted if agents feel protected from the risk of sanctions that non-normative behaviour might otherwise incur:
  - buyers or sellers may refuse to pay for, or provide, a resource after the other party has completed their part of the transaction;
  - a market-exchange could extort money from traders by either not allocating resources between them, or fabricating fraudulent transactions to increase profits.

In real-world exchange markets, these types of *counterparty risk*, are protected against by *regulatory bodies*, and ultimately *government*. Regulation enforces not just normative behaviour in market participants, but also ensures that market-mechanisms themselves behave correctly. However, in any open and dynamic system, regulation by a central authority is impractical, and perhaps prohibitive to the aim of maintaining a robust distributed system. In that case, *trust and reputation systems* have been seen as an approach for facilitating the self-regulation of multi-agent systems.

### 2.5.1 Notions of trust and reputation

Hardin defines trust as:

To say we trust you means we believe you have the right intentions toward us and that you are competent to do what we trust you to do.  
Hardin [70, p. 11]

In that respect, trust is a boolean property—you either trust someone or not. Further, according to this definition, trust is contextual: you may trust an entity to provide you with an Internet connection, but not to manage your financial affairs. Jøsang et al. [83] refers to this type of trust as *reliability trust*, and while there are other types of trust considered within the literature [82], they are all more specific instantiations of Hardin’s definition. The decision to trust another

## 2.5. TRUST AND REPUTATION ISSUES IN OPEN ELECTRONIC MARKETS

individual is made by first learning—through observation, in the most basic case—how *trustworthy* that individual is.

However, in large-scale distributed systems characterised by infrequent interactions with unfamiliar partners, assessing other individuals' trustworthiness can be challenging, if not impossible. In this case, *reputation* can be used as a mechanism to build trust within these communities, and encourage cooperative behaviours without the need for costly central enforcement [45]. Within these decentralised networks, reputation is the main tool for measuring trustworthiness; Jøsang et al. defines reputation as:

Reputation is what is generally said or believed about a person's or thing's character or standing.

Jøsang et al. [83]

While in distributed communities one may not have interacted with certain individuals before, and thus be unable to directly measure their trustworthiness, it is quite likely others have had direct interactions, and there is a general publicly perceived notion of that individual. Therefore, trust and reputation are different concepts, but reputation can be used in large-scale communities to measure another individual's trustworthiness in the absence of directly gathered information. From a system-wide or societal viewpoint, reputation acts in two fundamental roles:

The primary objective of reputation mechanisms is to enable efficient transactions in communities where cooperation is compromised by post-contractual opportunism (moral hazard) or information asymmetries (adverse selection).

Dellarocas [45]

Thus, reputation seeks to notify agents of those who are attempting to behave in a non-normative way, and punish those who do by labelling them as appropriately.

### 2.5.2 Trust and reputation approaches in electronic markets

Any trust and reputation approach within a multi-agent system relies upon the ability of information to spread between agents within the system. In comparison to real-world communities, online interactions introduce new challenges [44]. Some of these new challenges involve, for example: (i) *identity*: ensuring agents and their reputations belong together [46]; (ii) *interpretation*: understanding in what context the reputation information applies, e.g., based on the behaviour of the providing agent [166]; (iii) *accuracy*: ensuring that reputation information is honest and correct [85]; and (iv) *provision*: incentivising agents to provide reputation information at all [44]. From a mechanism design perspective, for example, mechanisms have been designed to incentivise the provision of honest feedback. Miller et al. [106] have shown that a central mechanism using scoring rules and side payments can elicit honest feedback from agents. With such information, *trust-based mechanism design* approaches such as [40] could be used to optimally allocate resources while taking into account the trustworthiness of agents. Aside from the underlying assumptions on agents, any mechanism that relies upon a central *trusted* third-party will not scale well across large-scale systems and themselves require regulation.

In more practical settings there are perhaps two main approaches for facilitating agents' trust or reputation based decisions within electronic markets. The first is to model trustworthiness or reputation from a *cognitive* perspective, which involves agents reasoning about their *beliefs* in other agents' desires or abilities in certain contexts. Different approaches for achieving this have been considered for online settings, e.g., using subjective logic [82] or argumentation approaches [129]. While cognitive approaches are a viable future direction, it is unclear how well they would currently, for example, accurately model the beliefs of all agent types that could potentially exist in a large open multi-agent system [73].

## 2.5. TRUST AND REPUTATION ISSUES IN OPEN ELECTRONIC MARKETS

The second approach is to calculate trustworthiness as degrees of *uncertainty* about the expected future behaviour of agents. These probabilistic approaches tend often to be grounded within Bayesian statistics [108, 109, 80, 81], and involve two methods. The first is to consider the trustworthiness of individuals as processes which can be modelled over continuous distributions. Often a distribution such as the Beta distribution is used, because it takes two shape parameters which can be used to represent positive and negative outcomes to previous interactions. Typically, an agent considers the expected value and its confidence to calculate its trustworthiness in another agent. An agent can then form a reputation of a target agent by combining the trustworthiness they have in the target, with the trustworthiness others have in the target. Several researchers have recently extended this approach to consider *subjective* reputations [165, 97]. In such models, *recommendation distributions* are maintained by each agent that *weight* the opinions of others according to how accurate their opinions have been in the past. In that case reputations become subjective—the same agent’s reputation can be considered differently by various agents. This approach has been applied to identifying either malicious or noisy opinions within a multi-agent system, allowing them to be ignored in the calculation of reputations.

### **Trust and reputation approaches in double auction markets**

In terms of reputation approaches for models involving double auction mechanisms, only a small amount of work exists within the literature. van Valkenhoef et al. [170] consider a two-stage CDA mechanism whereby buyers and sellers shout offers as usual, however, whenever the auctioneer matches two traders, the buyer is given the opportunity to measure the trustworthiness of the associated seller before committing to the trade. Trustworthiness represents a probability of resource delivery on the seller’s part, so when buyers only commit to trades in which their expected utility is positive, efficient allocations are achieved. Lu et al. [98] look at a clearing house auction where the auctioneer not

only determines the set of traders to be matched, but also sorts them by reputation, such that the most reputable traders get to trade with each other.

Neither of these approaches consider the behaviour or trustworthiness of the market-mechanism itself and, in an environment containing multiple competing marketplaces, there may certainly be a need for *market-exchange reputations*, when one considers them to be self-interested agents within a distributed and open multi-agent system. Finally, the efficiency of markets is considerably affected by both the volume of traders within them, and also the *type* of traders. None of the reputation approaches have studied the impact that making a large population of traders aware of the general profitability of market venues will have on the efficiency of the market-based system, and attracting the right and wrong types of traders to markets.

## 2.6 Summary and Conclusions

To summarise, system-centric approaches to computational resource allocation are prohibitive and limiting when one considers the expected growth and demand for resources in the future [63]. The large number of (likely mostly idle [124]) individual machines across the Internet, makes them potentially a huge untapped source of computational power, if users can be economically incentivised to provide their resources. Such a scenario would open up the possibility of large-scale distributed utility computing environments, where individual users can consume and provide computational resources, delivered across the Internet [19]. However, unlike current system-centric models of computational resource allocation, which assume full knowledge of the supply side of the market, allocation mechanisms are required that don't require knowledge of global supply and demand schedules.

*Market-based approaches* [63, 22, 35] have been proposed as a way of achieving this. The *continuous double auction* (CDA) is an elegant mechanism

## 2.6. SUMMARY AND CONCLUSIONS

which, when coupled with almost minimally intelligent [33] traders, achieves highly efficient allocations, unlike more decentralised market mechanisms such as posted-offer or bargaining models. In contrast to other centralised auction mechanisms, multiple CDA mechanisms can be distributed throughout an environment and, as long as traders can migrate between marketplaces, efficient allocations can be maintained [23]. Unfortunately, because computational resources are naturally *multi-attribute* in nature, and multi-attribute double auction mechanisms require computationally prohibitive algorithms to efficiently allocate resources, a novel approach is required. One approach that has not received attention is to consider the allocation of multi-attribute resources using multiple competing marketplaces. Within such an approach, multiple market-exchanges would compete to attract traders to their resource markets, where a particular type of computational resource is traded, and traders would choose to trade in markets that best satisfy their preferences and constraints. Several research challenges reveal themselves in such a model, for example in the design of market-exchange mechanisms for choosing the types of resources to be traded within their markets; approaches for designing and analysing mechanisms to meet these challenges are needed.

Empirical agent-based approaches, within the paradigm of multi-agent systems [183], have been proposed as a way to better design and analyse market mechanisms. In that vein, simulation frameworks for the specific study of market mechanisms in both isolation [76] and in competition [118] have been implemented, and several international market design tournaments have been launched [24]. However, neither analytic nor simulation models have been developed for studying the allocation of multi-attribute computational resources via competing marketplaces. In terms of designing and analysing competing market mechanisms in simulation, progress has been made by studying the results of CAT tournaments. However, while these tournament approaches are useful for analysing performance within certain environments, the brittleness of



some market mechanisms previously championed has been noted [116], and less attention has been given to how the *general* performance of mechanisms might be better measured. Finally, within any open multi-agent system there may be issues involving how to signal the expected behaviour of self-interested participants, or how to incentivise normative actions. While trust and reputation mechanisms have been cited as an excellent approach in general to electronic markets, little if any attention has been given to how these approaches can be specifically applied to selecting between marketplaces, and the impact that reputation has on the efficiency of allocations within those markets.

In conclusion, there is a need to investigate new approaches to multi-attribute computational resource allocation within distributed and open environments. Neither traditional system-centric approaches, or fully decentralised or centralised market-based approaches, are particularly suitable to the resource allocation scenarios considered. This thesis aims to contribute a better understanding of suitable market-based approaches to multi-attribute computational resource allocation by studying a novel and interesting approach, which relies on multiple competing marketplaces to provide markets for specific types of computational resource.

## CHAPTER 3

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# GENERALISATION PROPERTIES OF COMPETING MARKETPLACES

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The review carried out in Chapter 2 reveals a gap in the literature. There is no clear methodology for assessing the generalisation properties of competing market mechanisms. While economic mechanism design provides tools for dealing with this generalisation issue, through the design of incentive compatible mechanisms that generalise across all environments, these theoretical approaches only allow mechanisms to be designed for very restrictive settings, and competition between market mechanisms has not been considered. The first research objective of this chapter is to develop a methodology for analysing the generalisation abilities of competing market mechanisms. Such a methodology is important for designing and analysing many types of competitive market mechanism in simulated environments, where the generalisability of results is very important [100]. In that vein, a methodology of this type will be particularly useful to support other experimental simulation work later on in the thesis.

As discussed in Chapter 2, launched in 2007, the *TAC Market Design Tournament* [24] (CAT Tournament) has been used as a tool to encourage research into double auction mechanism rules. Entrants to CAT tournaments provide market mechanism agents called specialists, who must attract as many traders as possible to their market. Each CAT game consists of potentially hundreds of different trading agents (provided by the organisers), and multiple competing specialist agents (provided by the entrants). The rich environment created by, not only many traders competing with each other, but also many market mechanisms competing to attract traders, creates a potentially excellent test-bed for evaluating the effects of different double auction market mechanism rules, as used by the specialists. However, within such a complex environment, it may be the case that specialist performance is dependent on, or correlated with, some environmental factors. Given this, specialists may therefore be considered *brittle* (or obversely, *robust*) if their performance greatly depends (or does not) on environmental factors. The second research goal within this chapter is to better understand the characteristics of the mechanisms used by the specialists,

### 3.1. MOTIVATION AND RESEARCH QUESTIONS

particularly in relation to the environmental contexts in which they operate. Thus, within this chapter simulation analyses undertaken using the CAT Tournament platform JCAT<sup>1</sup> are described, using some of the specialists entered into the 2008 and 2009 CAT tournaments. Importantly, these analyses follow the novel methodology presented within this chapter.

This chapter makes several main contributions. Firstly, it provides a methodology for measuring, both quantitatively and qualitatively, the generalisation ability of specialists within CAT tournaments. Secondly, by using this methodology, it demonstrates that the specialists in the CAT Tournaments are not robust against a number of environmental changes. For several of these environmental factors, a change in them leads to some changes in the tournament ranks and/or the game scores achieved by the specialists.

The rest of this chapter is organised as follows. Section 3.1 outlines the main motivation for this work, as well as the research questions that this chapter aims to answer. In Section 3.2 a summary of the CAT tournament is provided for the reader, including how the games progress, and the metrics used to measure specialist performance. Section 3.3 presents an empirical evaluation of the generalisation abilities of some of the previous specialist market mechanisms submitted to the 2008 and 2009 CAT tournaments, using a novel methodology. The main research findings are that the specialists entered into the 2008 and 2009 tournaments are sensitive to a number of environmental factors, and thus can be said not to generalise well. The chapter ends in Section 3.4 with some conclusions and proposals for future work.

## 3.1 Motivation and Research Questions

Niu et al. [116] provided the first analysis of entrants from the first CAT tournament, which took place in 2007. Based on some insights into the CAT game,

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<sup>1</sup><http://jcat.sourceforge.net/>

Niu et al. developed a new specialist called MetroCat. Using all of the entrants from the 2007 tournament, along with their own MetroCat specialist (which had not been encountered by the 2007 entrants), Niu et al. found that none of the 2007 entrants, including the winning specialist, performed as well as MetroCat. Thus, Niu et al. have shown that the well-performing 2007 CAT specialists can have weaknesses in other situations. Niu et al. only considered how a new competitor (MetroCat) impacted on the performance of other specialists. However, there are other environmental factors that could impact on the performance of a specialist, including the types of traders in the environment, and how the game is scored. One motivation for the work within this chapter then, is to assess the impact that other environmental factors have on the performance of specialists.

Because they are typically entered over the Internet, each simulated day within a CAT game takes a non-trivial amount of time to complete; this is to allow participants to receive simulation information, and make potentially complex decisions. Thus, CAT games generally take a long time to complete—usually between 5–8 hours. Because there are several potential environmental factors of interest, there is a *state-space* explosion in the number of potential game configurations, making it unfeasible to simulate all possible configurations. Another motivation for the work in this chapter, then, is to provide a methodology for assessing the generalisation performance of specialists, or any other market mechanisms situated in complex environments, without the need to run all possible simulation configurations.

Within other trading-based competitions, some methodologies have been proposed to tackle similar problems. For example, Vetsikas and Selman [172] described a methodology for deciding on the best bidding strategy that their trading agent, WhiteBear, should use in the *Trading Agent Competition* (TAC) classic game<sup>2</sup>. Given a reduced set of possible initial ‘base-strategies’, Vetsikas and Selman face the issue of finding the best combinations to create an overall

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<sup>2</sup><http://www.sics.se/tac/page.php?id=3>

### 3.1. MOTIVATION AND RESEARCH QUESTIONS

successful bidding strategy for participating in many simultaneous auctions. Although this approach is sensible when trying to decide on the best strategy from an initial set of possible strategies, it is unclear how well such a best strategy would fare against *unseen* strategies, i.e., other competitors in the trading competition. Wellman et al. [176] also explore the idea of using a reduced strategy space to allow them to evaluate potential strategies taken from their TAC agent, *Walverine*. While they acknowledge that a strategy's performance does depend on those of its competitors, they hypothesise that an agent's performance should be relatively insensitive to the frequency of competitors using identical strategies. Their methodology consists of efficiently searching a reduced strategy space to find better performing strategies. Both Vetsikas and Selman's and Wellman et al.'s approaches are appropriate when considering a fixed initial space of potential strategies, however neither provide mechanisms to test the robustness of a strategy in the presence of *unseen* competitors.

The CAT game is more complicated than the original TAC game because there are two interacting populations—specialists and traders, both of whom contain (or could contain) members able to learn and/or evolve, and who are unknown in advance. Thus, an approach is needed to deal with domains where there are *coevolving* populations of competing agents, to offer insights into the robustness of the strategies in those populations.

The main research questions answered within this chapter are:

- *How can market mechanism generalisation performance be assessed quantitatively and qualitatively in complex simulated environments with many possible variables or factors?*
- *What are the generalisation properties of specialists within the CAT Tournaments? Are all specialists robust to all environmental factors?*

## 3.2 The TAC Market Design (CAT) Competition

The full organisation and structure of the TAC Market Design (CAT) Tournament is given in the game documents [24]. In this section, however, the most important aspects will be provided. A CAT game takes place over a number of simulation *trading days*, each of which consists of a number of *rounds*. Each round lasts a number of *ticks*, measured in milliseconds. The game uses a client server architecture, with the CAT server controlling the progression of the game. CAT clients are either traders (potential buyers or sellers) or specialists, i.e., marketplaces. All communication between traders and specialists is via the CAT server.

In the standard CAT installation, four different trader strategies are provided. *Zero Intelligence – Constrained (ZIC)* traders [66] shout randomly generated prices into the market, subject to some constraints. *Zero Intelligence Plus (ZIP)* traders [33] were previously discussed in Section 2.3.2. *RE* traders [52] use a reinforcement learning algorithm based on a model of human learning, with the most recent surplus or loss guiding the trader’s shouting strategy one step ahead. Finally, *GD* traders [65] use past marketplace history of submissions and transactions to generate beliefs about the likelihood of any particular bid or ask being accepted, which is used to guide shouting strategies. ZIC are the least, and GD are the most, sophisticated of these four types. In addition, all types of traders in the standard CAT installation use an n-armed bandit strategy [142] for selecting which specialist to register with on each new trading day<sup>3</sup>.

As discussed in Section 2.4.1, based on Niu et al.’s [116] rule framework, specialists have freedom to set market rules in six broad policy areas, covering: charging; quoting; shout accepting; trader matching; transaction pricing; and trade clearing. Within the game, competing specialists are not aware of the exact

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<sup>3</sup>An n-armed bandit strategy assumes a finite set of possible actions and learns reward distributions for each action over time. The desire is to balance exploration in order to more accurately learn reward distributions, and exploitation of the currently best reward distribution. The general n-armed approach is discussed in more detail in Section 5.2.1.

### 3.2. THE TAC MARKET DESIGN (CAT) COMPETITION

policies or strategies that their competitors are using, through they may attempt to learn them from observing behaviour. Specialists know that each trader in the environment is one of the four types, but not the overall proportions of each type within the trader population. Accordingly, the design of a specialist seeking to win the game cannot be optimised for only a subset of trading strategies.

In addition, the scoring metric used by the game is multi-dimensional. Games are scored using an unweighted average of three criteria: the proportion of traders attracted to the specialist each day (market share); the proportion of accepted shouts which are matched (transaction success rate); and the share of profits made by the specialist. A specialist's tournament score is the sum of its daily scores for all scoring days; it is important to note that not all trading days are scoring days, and specialists are unaware which these are in an attempt to prevent start-game and end-game effects. Specialists are ranked in descending order of their total scores, with the specialist in rank one declared the winner of that tournament.

As with trader types, the scoring multi-dimensionality creates challenges for the optimal design of specialists, since these criteria may conflict. A game-winning strategy may focus on scoring highly on different criteria at different times in the life-cycle of a game, or against different trader types. As was discussed in the introduction to this chapter, given this structure it is easy to see that some specialists may perform better with traders of a particular type, and/or against competing specialists using particular policies. Further, each CAT Tournament is generally only conducted over a limited number of different games (typically, three), thus a specialist's performance in a tournament is not necessarily a good guide to that specialist's *general* ability, i.e., with other trader mixes, or in competition against different specialists not included in that particular tournament.



### 3.3 Empirical Evaluation of Entries' Generalisation

#### Ability

The generalisation ability of specialists is tested using the following methodology. Unlike the official CAT tournaments, where entrant specialists are evaluated on a small subset of randomly chosen environments, in this work, specialists are evaluated on a range of carefully chosen environments, based on three different environmental contexts:

- *trader context*: the proportions of the four trader types in the trader population;
- *competitor context*: the members of the population of competing specialists;
- *scoring context*: the days over which scoring takes place (defined by length and start day).

By using different combinations of these three contexts, different tournament variations can be generated to evaluate specialists in. Within each context, because there are so many possible combinations/variations, it is proposed to reduce this space by focussing on extreme (or boundary) cases. For example, typical trader contexts might include using *all* of one type of trader and *none* of any others, or using only the most intelligent traders (which would be GD traders given the four types described in Section 3.2). It is hypothesised that by, for example, entirely excluding or exclusively including certain environmental factors, it is more likely to observe any sensitivities within specialists.

To show that some specialists' performances can be sensitive to a number of environmental factors, and in some cases generalise poorly, specialist performance was measured across different tournament variations in two ways. Firstly, by measuring the *qualitative impact* that tournament variations have on each specialist's performance; which was achieved by comparing rankings of specialists' mean scores for different (comparable) tournament configurations.

### 3.3. EMPIRICAL EVALUATION OF ENTRIES' GENERALISATION ABILITY

Secondly, by measuring the *quantitative performance impact*, i.e., the change that tournament variations have on each specialist's score. Since the differences introduced between tournament variations, e.g., the proportions of trader types in the trading population, itself contributes to the performance of the specialists, one cannot simply compare the mean scores of specialists over tournament variations and confidently state how the specialists are able to generalise between the two cases.

This is addressed by defining a new statistic to measure the performance of one specialist relative to others, across a diversity of tournament variations. The statistic, which is called the *normalised performance delta* of a specialist, denoted  $\hat{\delta}_i$ , provides a metric for analysing how a given tournament configuration affects the performance of the specialist. To calculate this statistic, for each specialist  $i$ , the normalised mean score  $\hat{\mu}_i$  is first calculated:

$$\hat{\mu}_i = \frac{\mu_i}{\sum_{j=1}^m \mu_j}$$

For a single specialist  $i$ , given two normalised scores  $\hat{\mu}_i^x$  and  $\hat{\mu}_i^y$  from two tournament variations  $x$  and  $y$ , the absolute difference  $d_i^{xy}$  between the two scores can be calculated:

$$d_i^{xy} = |\hat{\mu}_i^x - \hat{\mu}_i^y| \quad (3.1)$$

$d_i^{xy}$  provides a measure of how, with respect to other specialists in the tournament, a specialist  $i$ 's performance has changed from one tournament variation to the next. Finally, for each specialist  $i$  the normalised difference value  $\hat{\delta}_i$  is calculated.

$$\hat{\delta}_i = \frac{d_i^{xy}}{\sum_{j=1}^m d_j^{xy}} \quad (3.2)$$

In order to ascertain some statistical significance to specialist mean score values generated from multiple tournament runs, two-tailed paired t-tests of equality of

means were performed on certain pairs of specialists, in order to attempt to identify whether the reported rankings were distinct. In such cases both the *t-value* and *p-value* (using  $n - 1$  df.) are reported. The t-test statistical test assumes normality within the samples provided. Before any t-tests were run on the reported data, they were first subjected to the *Lilliefors Test* [95], a goodness of fit test for the Normal distribution. It was found that for all but one sample, which is highlighted when presented, the null hypothesis that the sample is normally distributed could not be rejected, with significance levels  $> 0.01$  in all cases. The non-normal sample was not required for direct comparison with any other, thus t-tests were found to be suitable for all comparisons between samples within the results reported in this chapter.

### 3.3.1 General experimental setup

Each JCAT simulation consists of a single tournament that runs for a number of trading days, with, in these experiments, 10 trading rounds per day, and 500ms per round. All experiments were carried out with both the JCAT server and all specialist clients situated on the same local machine. The trading population size was set at 400 traders, filled with traders taken from the four types described in Section 3.2. Buyers and sellers were split as evenly as possible in the different trader sub-populations. In order to achieve more statistically significant results for each tournament variation, each was repeated 15 times, using the same configuration, but with a different random seed. The specialist agents used in the experiments were downloaded in a pre-compiled form from the TAC Agent Repository<sup>4</sup>. Specifically, only entrants from the 2008 and 2009 competitions were used, except when this was not possible<sup>5</sup>.

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<sup>4</sup><http://www.sics.se/tac/showagents.php>

<sup>5</sup>Any specialist binaries entered into the 2008 or 2009 tournaments but not used in these experiments were either unavailable, or had issues affecting their ability to be used in experiments, such as execution or library problems.

### 3.3.2 Evaluation of the 2008 competition

For the analysis of the 2008 competition, the following specialists were included in the experiments: CrocodileAgent, DOG, iAmWildCat 2008, Mertacor1, Mertacor2, PSUCAT, PersianCAT and jackaroo. In the rest of this section they may be referred to as CR-08, DO-08, IA-08, M1-08, M2-08, PS-08, PC-08 and JA-08 respectively.

#### Over-fitting to trading population

The following set of results show that some specialists' performances are sensitive to different mixes of trader types in the trader population. Therefore, some specialists may be over-fitted to specific types or mixes of traders. For this set of experiments, all eight available specialists were used, and the scoring period included all 500 trading days. Using the previously described methodology, eight different trader mixes were identified, based on the notion of trader mixes consisting entirely of one of the four trader types, or entirely excluding one of the types.

Overall, it was observed that several of the specialists' final rankings were affected by trader mix variations, particularly Jackaroo, Mertacor1 and Mertacor2. Table 3.1 shows the results of two tournament variations, which are referred to as 'just-GD' and 'no-GD'. The just-GD variation consisted of a trading population made up of entirely GD traders, with equal buyers and sellers. In the no-GD variation, the trading population was composed of equal (as possible) proportions of RE, ZIP, and ZIC traders.

For a typical tournament variation, it was observed that in each of the 15 repetitions, scores, and thus rankings, were quite similar, leading to low  $\sigma$  values. It is, however, extremely unlikely that scores would ever be identical over all runs, due to the stochastic nature of the JCAT environment.

Table 3.1 highlights the fact that the overall rankings for the two tournament variations were different, most notably with changes in the middle

Specialist	Just GD Traders		No GD Traders		Rank	$\hat{\delta}$
	$\mu$	$\sigma$	$\mu$	$\sigma$		
PC-08	232.2	5.86	271.1	5.51	1, 1	0.355
M1-08	230.9	6.55	193.9	3.17	2, 4	0.364
JA-08	218.9	6.06	213.5	2.65	3, 3	0.064
M2-08	207.4	5.09	215.7	6.05	4, 2	0.067
IA-08	165.8	1.45	<i>165.1</i>	5.15	5, 6	0.016
DO-08	164.4	2.24	173.7	2.48	6, 5	0.078
CR-08	24.9	17.76	19.1	8.28	7, 7	0.057
PS-08	16.2	0.66	16.3	0.43	8, 8	0.001

Table 3.1: Mean, standard deviation, rank and  $\hat{\delta}$  values for a set of tournaments using the *just-GD* trader context and a set of tournaments using the *no-GD* trader context. First presented in [145]. One mean, for IA-08 and italicised was found to be from a non-normally distributed sample. However, it was not necessary to subject it to a statistical comparison with any other sample for the analysis carried out in this chapter.

and lower portions. Qualitatively, of particular interest was the change in rank between M1-08, M2-08 and JA-08. In simulations using the just-GD trader context, M1-08 was rank two and M2-08 rank four, while in the no-GD context the ranks were swapped to four and two respectively. In the just-GD case, a paired t-test of equality of means showed that the average scores of M1-08 and M2-08 were significantly different, with a *t-value* of 9.36 and a *p-value*  $< 0.001$ . The average scores of M1-08 and M2-08 were 230.9 and 207.4 respectively. In the no-GD case, a t-test resulted in a *t-value* of 14.04 and a *p-value*  $< 0.001$ . Mean scores in the no-GD case were 193.9 for M1-08 and 215.7 for M2-08.

Further, in the just-GD case, it was observed that M1-08 and JA-08 had ranks of two and three respectively, while in the no-GD case they had ranks of four and three. In the just-GD case, for M1-08 and JA-08, a t-test of equality of means resulted in a *t-value* of 19.09 and a *p-value*  $< 0.001$ , with mean scores of 230.9 for M1-08 and 218.9 for JA-08. In the no-GD case, a t-test reported a *t-value* of 4.20 and a *p-value*  $< 0.001$ , with mean scores of 193.9 for M1-08 and 213.5 for JA-08.

Finally, note that even a simple change of the trading population, i.e., when

### 3.3. EMPIRICAL EVALUATION OF ENTRIES' GENERALISATION ABILITY

Specialists	Just ZIC Traders		No ZIC Traders		Rank	$\hat{\delta}$
	$\mu$	$\sigma$	$\mu$	$\sigma$		
PC-08	276.2	11.47	244.1	4.53	1, 1	0.419
JA-08	218.6	4.71	214.6	2.49	2, 3	0.071
M2-08	213.9	8.20	224.7	5.77	3, 2	0.109
M1-08	192.1	2.72	207.0	3.76	4, 4	0.160
DO-08	170.7	2.62	180.0	2.32	5, 5	0.095
IA-08	161.6	5.15	170.7	4.09	6, 6	0.094
PS-08	16.9	0.46	16.2	0.47	7, 8	0.010
CR-08	16.8	5.07	20.4	7.90	8, 7	0.041

Table 3.2: Mean, standard deviation, rank and  $\hat{\delta}$  values for a set of tournament repetitions using the *just-ZIC* trader context, and a set of tournaments using the *no-ZIC* traders context. First presented in [145].

switching to using the just-GD trader context, can make a previous winner, PC-08, lose its winning edge. Statistically, PC-08 is not the clear winner in the just-GD case, though it was in the official 2008 CAT Tournament when a different trader mix was used. A t-test of equality of means between PC-08 and M1-08 in the just-GD case showed a *t-value* of 0.46 and a *p-value* of 0.65, with mean scores of 232.2 for PC-08 and 230.9 for M1-08. A counterpart to this situation is the no-GD case, where PC-08 clearly outperformed M1-08. Here the *t-value* was 38.31 and *p-value* < 0.001, with mean scores of 271.1 for PC-08 and 193.9 for M1-08. This highlights a situation where either PC-08 or M1-08 are particularly sensitive to the proportions of GD traders in the population. The  $\hat{\delta}$  values for PC-08 (0.355) and M1-08 (0.364) were considerably larger than those of the other specialists, showing a disproportionate change in performance over the two cases for both specialists.

In Table 3.2 the results of tournament using two more of the trader contexts, ‘just-ZIC’ and ‘no-ZIC’, are shown. Again, in both tournament configurations all specialists and scoring days were used; only the trader populations were varied. In the just-ZIC context only ZIC traders (equal number of buyers and sellers) were used, while in the no-ZIC variation, no ZIC traders were used and the population consisted of equal numbers of GD, RE and ZIP traders.

Running simulations using the just-ZIC and no-ZIC trader contexts

resulted in further situations where it is not statistically clear that the rankings between two specialists are the same across the two tournament variations, indicating that there were generalisation problems. In the no-ZIC case, M2-08 (rank two) outperformed JA-08 (rank three). A paired t-test of equality of means found the scores statistically different, with a *t-value* of 5.83 and a *p-value*  $< 0.001$ . The mean scores were 224.7 for M2 and 214.6 for JA. However, in the just-ZIC case, the mean scores between the two specialists, and thus the rankings, were not statistically distinct. A paired t-test resulted in a *t-value* of 1.75 and a *p-value* of 0.10. The mean scores were 213.9 for M2-08 and 218.6 for JA-08.

Table 3.2 also highlights a clear example of the performance impact that changes in the trader population can have on a specialist. The mean score for PC-08 in the just-ZIC case was 276.2, yet this dropped 8.83% to 244.1 in the no-ZIC case. While the makeup of the trader population can have a significant impact on the scores of specialists, in these two cases we see that other specialists' scores did not vary proportionally as much as PC-08's. By considering the performances changes of the other specialists, PC-08's normalised delta value  $\hat{\delta}$  was 0.419, which was considerably higher than the others'.

Highlighted in Table 3.3 are other qualitative impacts that different trader contexts had on specialists. In these tournament variations we considered the contexts 'just-ZIP' and 'no-ZIP'. Again, in both cases all specialists and scoring days were used in the simulations. The just-ZIP variation consisted of a trading population with only ZIP traders (equal number of buyers and sellers), while in the no-ZIP variation equal numbers of GD, RE and ZIC traders were used in the absence of any ZIP traders.

In the just-ZIP case M1-08 (rank three) outperformed M2-08 (rank four). A t-test resulted in a *t-value* of 10.35 and a *p-value*  $< 0.001$ . The mean scores for M1-08 and M2-08 were 208.0 and 189.0 respectively. However, in the no-ZIP case a different outcome is observed, with the ranks changed to two for M2-08 and four for M1-08. In this case, a t-test resulted in a *t-value* of 9.56 and a *p-value*  $< 0.001$ ,

### 3.3. EMPIRICAL EVALUATION OF ENTRIES' GENERALISATION ABILITY

Specialists	Just ZIP Traders		No ZIP Traders		Rank	$\hat{\delta}$
	$\mu$	$\sigma$	$\mu$	$\sigma$		
PC-08	255.7	12.18	255.9	5.17	1, 1	0.051
JA-08	231.3	5.02	211.5	4.37	2, 3	0.281
M1-08	208.0	5.86	199.0	4.19	3, 4	0.150
M2-08	189.0	5	221.9	6.94	4, 2	0.347
IA-08	169.7	3.16	173.5	4.34	5, 6	0.008
DO-08	164.1	4.86	179.7	2.4	6, 5	0.147
CR-08	17.0	6.35	16.1	5.04	7, 8	0.014
PS-08	16.2	0.65	16.3	0.4	8, 7	0.003

Table 3.3: Mean, standard deviation, rank and  $\hat{\delta}$  values for a set of tournament repetitions using the *just-ZIP* trader context, and a set of tournaments repetitions using the *no-ZIP* trader context. First presented in [145].

with means of 221.9 for M2-08 and 199.0 for M1-08.

#### Over-fitting to other specialists

In this set of experiments, the proportions of traders in the trader population remain fixed, i.e., the same trader context is used throughout. However, by running simulations using different competitor contexts, it is observed that some specialists' performances are sensitive to the presence of other specialists in the marketplace. For this set of experiments, the trader population context contained an equal mix of GD and ZIC traders. Since ZIC traders are the least, and GD the most, sophisticated trader types, using this mix may offer the most diverse trading, and hopefully challenging environment. In these tournaments, as with all the previously discussed ones, all 500 trading days were counted as scoring days.

In Table 3.4 the reader can see the impact of two different competitor contexts on the performance of some of the specialists. The first competitor context, called 'All Specialists', involves allowing all the specialists to take part in the tournament, while in the second context, called 'Top Three', only the three best performing specialists from the all specialists context are present in the tournaments. Of note is the effect that lower-ranked specialists had on the performance of higher ranked JA-08 and M2-08. For example, in the all specialists



Specialist	All Specialists		Top Three		Rank	$\delta^{\circ}$
	$\mu$	$\sigma$	$\mu$	$\sigma$		
PC-08	267.3	5.99	299.7	6.96	1, 1	0.361
JA-08	217.4	4.44	243.5	3.51	2, 3	0.293
M2-08	206.9	6.44	256.7	5.82	3, 2	0.347
M1-08	198.3	2.79	–	–	4, –	–
D0-08	174.4	2.81	–	–	5, –	–
IA-08	170.5	3.51	–	–	6, –	–
CR-08	18.8	5.21	–	–	7, –	–
PS-08	16.0	0.29	–	–	8, –	–

Table 3.4: Mean, standard deviation, rank and  $\delta^{\circ}$  values for a set of tournament repetitions using the *all specialists* competitor context, and a set of tournaments using the *top three* competitor context. The same trader and scoring contexts were used for each variation, consisting of an equal mix of GD and ZIC traders, and using all 500 scoring days. First presented in [145].

context, JA-08 outperformed M2-08 ( $t$ -value = 4.12,  $p$ -value = 0.001). Mean scores for JA-08 and M2-08 were 217.5 and 206.9 respectively. Alternatively, in the top three context, when lower ranked specialists are removed, and the remaining three specialists compete with each other over the same traders, the rankings of JA-08 and M2-08 switched ( $t$ -value = 8.30,  $p$ -value < 0.001). Mean scores for JA-08 and M2-08 were 243.5 and 256.72 respectively. Further, in Table 3.4 the reader may note that the total score, when aggregated across all specialists, is significantly different between the All Specialists and Top Three variations. The total amount of ‘score’ available to specialists should not be considered divisible across arbitrary numbers of specialists as within the JCAT framework due to the scoring system and trader behaviours.

Alternatively, in Table 3.5 the impact that *removing* the top three specialists has on the remaining bottom five becomes clear. For these two variants, the all specialists context was compared to the ‘bottom five’ context, where the top three specialists are removed. In a qualitative context, IA-08 did significantly better than D0-08 when the bottom five context was used, with a  $t$ -test revealing a  $t$ -value of 5.80 and a  $p$ -value < 0.001. The mean score for IA-08 was 215.0, while D0-08 scored 208.7. However, when the all specialists context was used, D0-08

### 3.3. EMPIRICAL EVALUATION OF ENTRIES' GENERALISATION ABILITY

Specialist	All Specialists		Bottom Five		Rank	$\hat{\delta}$
	$\mu$	$\sigma$	$\mu$	$\sigma$		
PC-08	267.3	5.99	–	–	1, –	–
JA-08	217.5	4.44	–	–	2, –	–
M2-08	206.9	6.44	–	–	3, –	–
M1-08	198.3	2.79	376.3	4.17	4, 1	0.525
DO-08	174.5	2.81	208.7	1.5	5, 3	0.198
IA-08	170.6	3.51	215.0	3.86	6, 2	0.217
CR-08	18.9	5.21	32.9	10.22	7, 4	0.044
PS-08	16.1	0.29	18.2	0.32	8, 5	0.016

Table 3.5: Mean, standard deviation, rank and  $\hat{\delta}$  values for a set of tournament repetitions using the *all specialists* competitor context, and a set of tournaments repetitions using the *bottom five* competitor context. The same trader and scoring contexts were used for each variation, consisting of an equal mix of GD and ZIC traders, and using all 500 scoring days. First presented in [145].

ranked higher than IA-08 ( $t$ -value = 3.31,  $p$ -value = 0.0051). The average score for IA-08 was 170.6, while DO-08 scored 174.5.

With respect to the performance impact that the two tournament variations had on specialists, it is clear that the inclusion (or likewise, exclusion) of the three specialists PC-08, JA-08 and M2-08 clearly affected the performance of M1-08 more than any of the remaining four. When the top three specialists were introduced in the all specialists context, all of the other specialists' scores were lower, however a high normalised delta value of 0.525 for M1-08 indicated it was considerably more sensitive to their presence.

#### Over-fitting to scoring period

In Sections 3.3.2 and 3.3.2 a fixed scoring period of 500 days was maintained, and either different competitor contexts or trader contexts were considered. In this section, examples showing that specialists are also sensitive to *scoring contexts* are presented. For the following simulations, the all specialists competitor context and the just-ZIC trader context were used. The two scoring contexts considered here were 'short-early', which means using trading days 1–100 as scoring days,

Specialist	Short-early (days 1–100)		Medium-middle (days 100–300)		Rank	$\delta$
	$\mu$	$\sigma$	$\mu$	$\sigma$		
PC-08	50.8	1.94	158.6	7.34	1, 1	0.190
M2-08	46.0	1.86	118.8	5.19	2, 3	0.025
JA-08	39.8	0.81	124.4	3.34	3, 2	0.150
M1-08	39.5	1.01	107.7	1.80	4, 4	0.056
IA-08	35.0	1.19	89.1	3.72	5, 6	0.011
DO-08	34.0	1.09	96.4	1.46	6, 5	0.069
PS-08	16.9	0.46	0.00	0.00	7, 8	0.251
CR-08	16.8	5.07	0.00	0.00	8, 7	0.249

Table 3.6: Mean, standard deviation, rank and  $\delta$  values for a set of tournament repetitions using the short-early scoring context and a set of tournament repetitions using the medium-middle scoring context. For all these simulations the just-ZIC trader contexts were used as well as the all specialists competitor context. First presented in [145].

and ‘medium-middle’, which means using trading days 100–300 as scoring days<sup>6</sup>. As would be expected, scores were lower when the short-early context was used because the scoring period (100 days versus 200 days) is smaller.

Table 3.6 shows the effect changing the scoring period had on the performance of the specialists. Many of the specialists’ ranks changed between simulations using the two scoring contexts. When the short-early scoring context was used, JA-08 had a rank of three, while M2-08 had a rank of two ( $t$ -value = 10.42,  $p$ -value < 0.001); mean scores were 46.0 for M2 and 39.8 for JA. Alternatively, if the medium-middle scoring context was used, the ranks of M2 and JA switched. Again, scores were statistically distinct, resulting in a  $t$ -value of 3.34 and a  $p$ -value of 0.004.

### 3.3.3 Evaluation of the 2009 competition

For the analysis of the 2009 competition, the following specialists were included in the experiments: Cestlavia (CE-09), Cuny.cs (CU-09), Jackaroo (JA-09), Mertacor (ME-09), PSUCAT (PS-09), TWBB (TW-09) and iAmWildCat 2009 (IA-09). As

<sup>6</sup>Short and medium refer to the length of the scoring period, while early and middle refer to the time during tournament when the scoring period is instantiated.

### 3.3. EMPIRICAL EVALUATION OF ENTRIES' GENERALISATION ABILITY

Specialist	Just GD Traders		No GD Traders		Rank	$\hat{\delta}$
	$\mu$	$\sigma$	$\mu$	$\sigma$		
CE-09	248.5	4.32	177.1	4.50	1,4	0.279
CU-09	200.5	6.15	158.6	6.86	2,6	0.171
JA-09	173.2	2.88	234.2	6.97	3,1	0.185
IA-09	168.5	2.84	160.8	3.22	4,5	0.049
ME-09	161.2	5.72	200.0	6.47	5,2	0.111
PS-09	138.6	9.15	178.4	2.52	6,3	0.117
TW-09	118.7	10.30	148.2	9.35	7,7	0.085

Table 3.7: Mean, standard deviation, rank and  $\hat{\delta}$  values for a set of tournaments using entrants to the 2009 CAT Tournament, with an environment containing just GD and no GD traders. First presented in [146].

with the 2008 entries, the specialists were subjected to a variety of tournament configurations using varying trading, competitor and scoring contexts. Overall, Jackaroo was a worthy 2009 champion, as not only did it win the official 2009 CAT Tournament, it won almost 80% of the tournament variants considered, although there was a considerable lack of generalisation in the other specialists.

However, there were some configurations that JA-09 was particularly sensitive to. Along with CE-09, particular sensitivity was shown to GD traders. Two different trader contexts were used here: 'just-GD', consisting entirely of GD traders, and 'no-GD', consisting of equal amounts of RE, ZIP and ZIC traders, with no GD traders used. Table 3.7 clearly shows that JA-09 performs relatively poorly when a just-GD trader context is used, while it regains its top spot when the no-GD trader context is used. Paired t-tests of equality of means between JA-09 and CE-09 reveal  $t\text{-value} = 52.5$  for just-GD,  $t\text{-value} = 24.47$ , and  $p\text{-values} < 0.0001$  in both cases.

#### 3.3.4 Evaluation of best performers and overall progress

In this section, the top three specialists from both 2008 and 2009 are taken, and compared against each other. Considering previous specialist performance, the three specialists with the highest mean scores from each of the two years were used. The specialists chosen from those entered in the 2008 competition were

Specialist	Just RE Traders		No RE Traders		Rank	$\hat{\delta}$
	$\mu$	$\sigma$	$\mu$	$\sigma$		
PC-08	230.1	5.75	153.1	5.72	1,6	0.481
JA-09	215.9	4.69	212.9	5.32	2,1	0.018
CE-09	189.4	3.10	189.5	4.43	3,4	0.001
ME-09	174.3	3.48	202.6	10.09	4,2	0.177
JA-08	169.0	3.25	178.4	3.91	5,5	0.059
ME-08	160.8	5.87	202.5	13.53	6,3	0.261

Table 3.8: Mean, standard deviation, rank and  $\hat{\delta}$  values for a set of tournament repetitions using the just-RE trader context and a set of repetitions using the no-RE trader context. In these cases, the top three specialists from 2008 and 2009 were pitted against each other. First presented in [146].

Persian Cat, Mertacor and Jackaroo. From the 2009 competition entries, Cestlavie, Jackaroo (09) and Mertacor (09) were chosen.

Overall, JA-09 was still generally the strongest specialist, though the performance of all specialists was much closer than when considering only 2008, or only 2009, specialists. Of particular interest, however, were two trader contexts involving RE traders. The first, ‘just-RE’ consists of using only RE traders, while the second, ‘no-RE’, consists of using equal numbers of GD, ZIP, and ZIC traders, with no RE traders used. Table 3.8 show that PE-08 maintained—as it did against 2008 only specialists—its top position when the just-RE trader context was used, but when the no-RE context was used, its rank, which was still first against 2008-only competition, plummeted to sixth. For the just-RE (no-RE) contexts, a paired t-test of equality of means between PC-08 and JA-09 returned a *t-value* of 6.34 (47.33) and, in both cases, a *p-value*  $< 0.001$ .

By applying the methodology in Section 3.3, to the evaluation of the generalisation properties of specialists, it has been discovered within this chapter that a once winning specialist can over-fit to previously unseen competitors, which would have been hard to identify without using such a methodology. This result is of further interest because in the 2009 only experiments, JA-09 won both the just-RE and no-RE cases, while in this case, an entry from the *previous year* outperformed it, suggesting previous competitor strategies had not been

### 3.3. EMPIRICAL EVALUATION OF ENTRIES' GENERALISATION ABILITY

Trader Mix	2008 Competition		2009 Competition		2008/9 Best	
	$\mu$	$\sigma$	$\mu$	$\sigma$	$\mu$	$\sigma$
Just GD	157.59	2.28	172.74	1.72	<b>187.33</b>	0.56
No GD	158.56	1.32	179.65	2.67	<b>186.43</b>	2.02
Just RE	160.52	2.25	182.00	1.22	<b>189.96</b>	1.98
No RE	158.13	0.66	181.03	2.09	<b>189.87</b>	1.66
Just ZIP	<i>156.37</i>	1.42	<i>167.24</i>	2.64	<b>179.56</b>	2.49
No ZIP	159.21	0.90	181.37	2.08	<b>190.54</b>	1.35
Just ZIC	158.35	0.97	179.72	1.80	<b>188.16</b>	2.11
No ZIC	159.71	1.14	181.18	2.13	<b>189.68</b>	1.59
GD/ZIC	158.75	0.89	180.33	1.79	<b>191.24</b>	1.59

Table 3.9: Mean overall specialist performance from tournaments using various trader contexts. The highest overall scores for each trader context are emboldened. Unsurprisingly, in all cases the 2008/09 best competitor context, consisting of the top three specialists from each year, came out on top. The trader context that resulted in the *lowest* overall specialist scores has been emphasised. It is of particular interest that in all three competitor context variations, the just-ZIP trader context results in the lowest scores. First presented in [146].

considered enough in the design of a new one.

One interesting question to ask is: what kind of overall progress is being made by specialists in general each year? It can be answered by considering the all specialists competitor contexts from 2008 and 2009, as well as the competitor context formed from combining the top three specialist of each year, and then analysing overall performance of all specialists against various trader contexts. From Table 3.9 it is clear that specialist performances against any of the trader contexts were on average higher for the 2009 entries than the 2008 entries, and that when only the best performers from the two years were evaluated together, the mean performance was even higher (emboldened in Table 3.9). However, it is not clear as to whether this performance increase is an indicator of improved specialist robustness, and thus year-on-year progress, or merely an artefact of the differing sample sizes between the groups (the 2008 competition results consider eight specialists, the 2009 seven, and the 2008/09 six).

Perhaps the most interesting finding, which would not have been visible without such extensive experimentation, was that in all cases the just-ZIP trader

context, consisting of a trading population of only ZIP traders, invoked the lowest mean scores all around. Intuitively, one might expect that GD traders, using a more sophisticated, and thus intelligent, strategy than ZIP, would be harder to perform well against. In the 2009 and 2008/09 cases, for example, a paired t-test of equality of means between the just-ZIP sample and the just-GD sample, returned a  $t$ -value = 6.66 for the 2009 case,  $t$ -value = 6.53 for the 2008/09 case, and  $p$ -values < 0.001 in both cases.

### 3.3.5 Discussion

This chapter has presented a methodology that allows one to evaluate and compare specialist agents' generalisation abilities systematically and quantitatively. It is believed that this approach is the first to allow such properties to be measured—especially in a *coevolutionary* context. This work is significant because without such an approach, it is hard to know the true performance of any particular agent strategy, as one cannot see how well a strategy performs against unknown or previously unseen competing strategies, i.e., how well a given strategy generalises and thus its robustness. Although some of the specialists generalise better than initially thought, this chapter's results show that some seemingly strong strategies can have weaknesses when competing with certain other strategies. This is interesting because it is clear from the literature that often 'best strategies' or 'best results' are published, and without any further elaboration on their generalisation ability, these results can be very misleading.

Results in this chapter also suggest that a seemingly less intelligent trading strategy such as ZIP can be harder to perform well against than a more intelligent one such as RE or GD. This is of particular interest because it suggests that competing teams may be putting too much emphasis on designing and testing specialists against only particular trading strategies. Thus, although it may seem obvious that the performance of any given strategy—whether in the CAT game or some other competitive multi-agent system—will depend on the

### 3.4. CONCLUSIONS

strategies being used by other agents, it is *never* clear how strong this dependency is, or the resulting quantitative values such a dependency provides.

To define what ‘robustness’ of a trading or specialist strategy means is not straightforward in the coevolutionary environment created by the CAT tournament, let alone to actually measure such a property in a systematic and rigorous way. The approach in this chapter, unlike others [172, 176, 116], is the first to look at how well such designed strategies generalise to previously unseen strategies, using the CAT competition as a case-study. It is hoped that this approach can be used for analysing the generalisation properties of strategies not only in other agent-based competitions involving competition between marketplaces, but also in any agent-based simulation models within a complex adaptive domain.

## 3.4 Conclusions

The generalisation ability of specialists (i.e., market mechanisms) has not been studied previously in the literature. Theoretical economic mechanism design approaches to designing robust incentive-compatible market mechanisms, which generalise across all trader strategies and types, involves assuming traders are strictly rational. However, computer software is always resource-constrained and bug-prone, thus the designers of computational mechanisms cannot assume that traders always act rationally or in their own self-interest. Moreover, economic mechanism design theory has not considered competition between mechanisms, and so has not explored competitive performance of mechanism features, nor the *generalisability* of these features over different competitive environments.

The research reported in this chapter has tried to explore the generalisation properties of market mechanisms, using the 2008 and 2009 CAT Tournament specialists as the basis. It is unclear whether and how a market mechanism might (intentionally or unintentionally) favour certain trading strategies, or facilitate or



inhibit other competing market mechanisms. A specialist which performs well under one particular tournament setup may not perform well if the setup changes slightly. Therefore, it is essential to study and understand any hidden bias that a specialist might have built into it. This was achieved by applying a novel methodology to assess the generalisation properties of the specialist market mechanisms. Specifically, many JCAT simulations were run, using a variety of configurations, including changing both the trader and specialists populations as well as changing the period used to generate specialist scores; importantly, specific configurations were used that encompassed *representative* contexts. This chapter shows for the first time how changes in the competition configuration can have an impact on specialists' performances in both a qualitative and quantitative context.

The results of this experimental work showed that specialists can be sensitive (and specialised) to a number of factors in the competition, including trader strategies, other specialists, and the scoring period. Such results indicate that an appropriate evaluation of such a competition (and other similar ones) would need a theoretically sound framework, which can measure specialists' generalisation abilities quantitatively. They also point out the importance in analysing the relationship between a winning specialist and the particular competition setup used, so that insights into what makes a specialist better/worse can be gained. Further, results in this chapter have shown that a trading strategy with less intelligence than others, i.e., ZIP, can be harder to score against, suggesting current specialists are concentrating on performing well against more intelligent trading strategies.

The contributions of this chapter are:

- a methodology for qualitatively and quantitatively measuring the generalisation properties of competing market-mechanisms (specialists) in coevolutionary trading environments.
- a statistic for measuring the relative performance change in comparable

### 3.4. CONCLUSIONS

CAT tournament variations.

- evidence that many specialists are not robust against changes in various environmental factors, and thus do not generalise well.
- evidence that current CAT entrants are possibly concentrating on designing specialists to only perform well against (apparently) more intelligent trading agents and other competitors.

Some of the materials presented in this chapter appeared as [145, 146]. In this chapter, three major issues were identified as having a significant impact on specialists' performance, from the viewpoint of generalisation. However, there are other issues to be considered, e.g., the performance (scoring) metric used in the tournaments. It would be interesting to study the potential trade-offs between, for example, market share and profit, perhaps using a multi-objective approach. In terms of a theoretical framework for measuring specialists' generalisation quantitatively, the possibility of adopting one for measuring strategies' generalisation ability [29] will be considered in the future.

Finally, although the CAT Tournament aims specifically to encourage research and development of automated design of double auction mechanisms, it is believed that the methods and techniques here have wider applicability. Traditional analysis of situations where individuals make strategic decisions that impact both their own and others' welfare is traditionally carried out using game theoretic methods [61]; often the intention is to define and study the equilibria present within the system of interest. Game theoretic analysis often requires full knowledge of the possible strategies players may take, along with full knowledge of the outcomes or payoffs of the interactions of these strategies, so that they may be evaluated in turn and the best strategy chosen. This very high rationality requirement means that traditional analysis is impractical in many settings due to the infinitely many preferences that agents may be required to keep within a complex system.

One approach to deal with this has been to use *Evolutionary Game Theory* (EGT) [102] as a framework for more accurately modelling the notion that less-than-rational individuals tend to adapt strategies over time in response to those being played by individuals around them, and that the dynamics created by in such an environment lead to the equilibria within the system. EGT has been applied with respect to multi agent systems [169] and more specifically in terms of analysing agents' strategies in economic games [133, 173]. While an improvement over traditional approaches EGT still requires the game being modelled to be *normal-form*, i.e., that there is complete information about all of the possible states of the game and associated payoffs. In many interesting games payoffs typically depend upon decisions taken by players previously, and converting these games to normal-form requires generating *huge* payoff matrices—typically impossible with current technologies. One approach to this problem, applied to the design of market-mechanisms, similar to those studied within this chapter, was to use *Empirical Game Theory* [137], whereby games with many strategies and/or stochastic payoffs can be analysed by *approximating* the payoff matrix in an offline way and then using typical evolutionary game theoretic approaches, such as replicator dynamics.

However, as discussed in Chapter 2, these game theoretic techniques have only been applied to analysing market-mechanisms in isolation, and even empirical game theory approaches can only deal with tens of agents within a system, while within this chapter multiple competing marketplaces attempting to attract hundreds of traders, are the subject of analysis. Indeed, many complex, adaptive domains, such as those in public policy or defence, have large sub-populations of intelligent entities who co-evolve or change dynamically in response to each other's actions, quickly making any analytical mathematical models intractable. Accordingly, these domains are typically studied using computer simulation methods, and the issue of generalisability of results then becomes of great importance [100]. The techniques described in this chapter

#### 3.4. *CONCLUSIONS*

potentially have application to these other domains, and further investigations will form future work.



## CHAPTER 4

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# A MODEL FOR COMPUTATIONAL MULTI-ATTRIBUTE RESOURCE ALLOCATION

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*The construction of an economic model, or of any model or theory for that matter (or the writing of a novel, a short story, or a play) consists of snatching from the enormous and complex mass of facts called reality, a few simple, easily-managed key points which, when put together in some cunning way, become for certain purposes a substitute for reality itself.*

—Evsey Domar

In this chapter, a model describing a novel approach for allocating distributed multi-attribute computational resources is presented. As discussed in Chapter 2, other fully centralised or fully decentralised approaches to multi-attribute resource allocation suffer from a number of issues, e.g., being reliant on a single mechanism that is non-distributable and complex, or relying on complex bargaining strategies, respectively.

Within this approach, computational resources are allocated across distributed, competing double auction marketplaces, which choose the type of resource to be traded within their market, while traders trade in the resource markets that most suit their preferences and constraints. While models and platforms for studying competition between marketplaces exist, e.g., JCAT [118], they only consider single-attribute resource allocation. Thus, this chapter is motivated by the need for a new model of both trader and marketplace behaviour, which will enable study of the proposed approach, because unlike previous models: (i) the resources are multi-attribute in nature, and traders have preferences and constraints over them; and (ii) marketplaces have to specifically choose what types of multi-attribute resources can be traded within their market. As discussed in Chapter 2, it is not possible to say if this approach is *generally better* than any other, because all models attempt to satisfy multiple objectives. As a result, direct comparisons with existing models would not be possible, although approaches to potential future comparative studies are discussed in Section 4.6.

While no explicit experimental work is carried out within this chapter, it forms an essential basis for empirical work carried out throughout the rest of the thesis, and hopefully for other researchers interested in designing mechanisms for distributed computational resource allocation. The main contributions of this chapter therefore are: (i) to propose and describe a novel method for multi-attribute resource allocation, based upon competing double auction marketplaces; (ii) to formally define trader decision-making behaviours, based upon marketing models grounded in consumer theory; and (iii) to provide a novel

#### 4.1. COMPUTATIONAL RESOURCE ALLOCATION

algorithm for solving an optimisation problem, which presents itself when a population of traders potentially have different preferences and constraints over multi-attribute resources.

The rest of this chapter proceeds as follows. In Section 4.1, multi-attribute computational resources are formally described, along with the expected method of their allocation. In Section 4.2, the expected decision-making behaviour of the agents in the system is defined, using multi-attribute utility functions. In Section 4.3 and Section 4.4, the *mechanics* of the agents are described, including the double auction policies, market-selection, and trading strategies. In Section 4.5 the problem of measuring the allocative efficiency within the system is identified, and a novel algorithm for measuring the utility of an optimal allocation is defined. Finally, the chapter is concluded in Section 4.6.

### 4.1 Computational Resource Allocation

Computational resources are often specified to meet both *functional* and *non-functional* requirements [189]. Functional requirements—as well as *some* non-functional requirements—can be easily quantified and commoditised, e.g, processing power, memory capacity and storage capacity. Thus, many types of computational resources could be accurately specified in terms of a bundle of *attributes*. This model considers *abstract* computational resources, only assuming that a resource comprises a vector  $\pi$  of  $n$  non-price attributes:

$$\pi = \langle \pi_1, \pi_2, \dots, \pi_n \rangle, \quad (4.1)$$

where  $\pi_i \in [0, 1]$  refers to the *attribute-level* of the  $i^{\text{th}}$  attribute. Resources can be differentiated by their *type*, which is defined by the levels of each of their attributes. Two resources can be considered identical *iff* all of their



attribute-levels are equal:

$$\boldsymbol{\pi}^1 \equiv \boldsymbol{\pi}^2 \iff \forall_j, \pi_j^1 = \pi_j^2$$

Different consumers will have varying minimum resource requirements, which must be satisfied in order that the resource is useful to them. Realistically, these requirements might fall upon a minimum level of storage or random-access memory for large data-oriented tasks, or processing power for time-sensitive tasks. A user can impart these requirements on their trading agent  $a_i$  using a vector  $\mathbf{r}_{\downarrow}^{a_i}$  of *minimum constraints*:

$$\mathbf{r}_{\downarrow}^{a_i} = \langle r_{\downarrow 1}^{a_i}, r_{\downarrow 2}^{a_i}, \dots, r_{\downarrow n}^{a_i} \rangle, \quad (4.2)$$

where  $r_{\downarrow j}^{a_i}$  is, for example, the minimum level attribute  $j$  must meet in order to be useful to  $a_i$ .

As well as minimum constraints, consumers might *not* require certain attribute to be above specific thresholds, e.g., because their tasks only require a certain amount of memory to run. Likewise, providers may have constrained hardware or capacity, and may only be able to provide certain attribute-levels to consumers; a user's laptop-based resource has different maximum attribute-levels to a node on a high-speed computational cluster, for example. Again, these requirements can be communicated to trading agents via a vector  $\mathbf{r}_{\uparrow}^{a_i}$  of *maximum constraints*:

$$\mathbf{r}_{\uparrow}^{a_i} = \langle r_{\uparrow 1}^{a_i}, r_{\uparrow 2}^{a_i}, \dots, r_{\uparrow n}^{a_i} \rangle, \quad (4.3)$$

where  $r_{\uparrow j}^{a_i}$  is the maximum constraint on attribute  $j$ , and  $\forall_j, r_{\uparrow j}^{a_i} \geq r_{\downarrow j}^{a_i}$ . As well as expressing preferences over different resources, multi-attribute decision theory states that decision-makers might have preferences over the individual attributes of a resource [84]. For consumers, represented by buying agents, preferences describe the relative importance of each attribute, in terms of value. For

#### 4.1. COMPUTATIONAL RESOURCE ALLOCATION

providers, represented by selling agents, preferences describe the relative *cost* of providing each of the attributes. It is assumed each trader  $a_i$  maintains a vector  $\mathbf{w}^{a_i}$  of preferences over the attributes of a resource:

$$\mathbf{w}^{a_i} = \langle w_1^{a_i}, w_2^{a_i}, \dots, w_n^{a_i} \rangle, \quad (4.4)$$

where  $\forall_j, w_j^{a_i} > 0$  and  $\sum_{j=1}^n w_j^{a_i} = 1$ . If the trader  $a_i$  does not have preferences over the different attributes, equal weighting is applied to all attributes:

$$\mathbf{w}^{a_i} = \langle \frac{1}{n}, \frac{1}{n}, \dots, \frac{1}{n} \rangle.$$

##### 4.1.1 Trading resources in distributed marketplaces

Within this model, *market-exchange* agents provide markets for trading agents to buy and sell computational resources. To simplify analysis, a basic assumption made, is that each market-exchange provides a single instance of a market, in which resources are allocated using a double auction mechanism.

Market-exchanges, along with trading agents, are considered to be self-interested expected utility maximisers. Traders' tasks are to maximise utility by either buying or selling resources for as little or as much (respectively), as possible.

Market-exchanges, on the other hand, charge fees to traders in return for access to their market. Different fee structures can have significant impacts on attracting, or not, traders to a market. Three main types are considered within this model:

- *registration fees*: are charged to traders in exchange for permission to enter the exchange's market and shout offers. They are charged once per trading day.
- *transaction price fees*<sup>1</sup>: are charged to traders who successfully transact in the market. The fee is a percentage of the transaction price, payable by both traders involved.
- *spread commission fees*: again applicable to traders who successfully transact, the spread is the difference between the two trader's individual offers. The spread commission fee is a percentage of the difference between these two prices.

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<sup>1</sup>In some parts of the literature this type of fee is known as Ad Valorem—"according to value".

A variety of charging structures could have been implemented; the three chosen are inspired by the CAT [24] tournament model: JCAT [77]. It is believed that by covering market entry, and transaction-based fees, a realistic charging structure has been used. As discussed in Chapter 2, rather than allocating resources via a single centralised mechanism, segments of the market could be satisfied by distributed marketplaces, each offering a market for trading a particular type of resource. Dependent on their preferences and constraints, traders migrate to the marketplaces that most suit them. Thus, within the model, market-exchanges must—aside from running an auction mechanism—decide each trading day the *type* of resource to be traded within its market. Given the charging structure above, market-exchanges have an incentive to attract traders to their market, as well as ensuring that as many traders as possible can trade the resource specified by the market-exchange. Given this, resource type selection, achieved through attribute-level selection, is *vital*.

### The trading process

Market-based systems are often complex, containing many economic agents adapting and/or learning over time. Within the current model, it is assumed there exists a set of trading agents  $\mathcal{T}$  and a set of market-exchange agents  $\mathcal{M}$ . The trading agents are assumed to consist of sets of buyers  $\mathcal{B} \subset \mathcal{T}$  and sellers  $\mathcal{S} \subset \mathcal{T}$ . Throughout this thesis, traders are generally referred to as  $a_i \in \mathcal{T}$ , however, in some cases a buyer may be explicitly defined  $b_i$ , or a seller  $s_j$ . The market-based system progresses each trading day via a number of stages, as follows:

1. *Attribute-level selection stage*: at the beginning of the *trading day*, each market-exchange defines the type of resource to be traded in its market, by selecting, and then broadcasting, the attribute-levels of that resource.
2. *Daily market selection stage*: next, traders decide which of the market-exchanges they wish to join; traders may only join at most one exchange per trading day.
3. *Trading and trader learning stage*: the trading day is split into a number of *trading rounds*—opportunities to shout offers into the market.

## 4.2. DECISION MAKING MODELS FOR AGENTS

4. *Venue learning stage*: at the end of the trading day traders and market-exchanges calculate their daily profit. This is used as a signal to the decision mechanisms that dictate behaviour on the next trading day.

Each transaction  $\theta$  executed by a market-exchange, can be represented as an ordered 7-tuple that specifies: the buyer  $\theta_b$  and seller  $\theta_s$  involved in the transaction; the market-exchange  $\theta_m$  executing the transaction; the matching bid  $\theta_{bid}$  and ask  $\theta_{ask}$  offers; the transaction price  $\theta_\tau$ ; and the type of resource exchanged  $\theta_\pi$ .

$$\theta = (\theta_b \in \mathcal{B}, \theta_s \in \mathcal{S}, \theta_m \in \mathcal{M}, \theta_{bid}, \theta_{ask}, \theta_\tau, \theta_\pi) \quad (4.5)$$

## 4.2 Decision Making Models for Agents

As discussed in Chapter 2, software agents need to be able to reason over many states, in order that they can make decisions appropriate to completing their task. Thus, within this market-based system, buyers and sellers need to have a decision-making model that allows them to state their preferences over various multiple-attribute computational resources. An agent's preferences over the types of resources defined in Section 4.1 can be formally defined using a multi-attribute utility function, which allows a decision maker to get a conjoint utility measure for a multi-attribute resource, based upon each of the individual attribute utilities, by combining them according to relative importance.

### 4.2.1 Trader multi-attribute utility functions

Recently, other agent-based computational resource allocation models, e.g., [11, 13, 93], have proposed that agents make use of the additive multi-attribute utility function introduced by Keeney and Raiffa [84], which, using their notation, is of the form:

$$u(\mathbf{x}) = \sum_{i=1}^n k_i u_i(x_i), \quad (4.6)$$

where  $u$  and  $u_i$  are the utility functions for the entire resource  $\mathbf{x} = \langle x_1, x_2, \dots, x_n \rangle$  and each individual attribute  $x_i$  respectively. The utility of each attribute is weighted according to its preferences or importance to the decision maker; the weight of attribute  $i$  is represented by  $k_i$ . However, additive functions of this type, while combining attribute utilities according to relative importance, fail to consider one important computational resource assumption, viz. that worthless resources, with attributes failing to satisfy minimum constraints, should provide zero utility. It is clear from Equation 4.6 that no matter what the utility of individual attributes, it is not possible for one attribute  $x_i$  to determine the entire resource utility, because the utility function is purely additive.

In order that computational resource consumers' constraints on minimum attribute levels can be realistically modelled, a richer utility function is now introduced that enforces the assumptions about buyers' preferences over resources with attributes that fail to meet these constraints. Formally, a buyer  $b_i$ 's valuation of a resource  $\pi$  is determined according to the following multi-attribute valuation function  $v_{b_i}(\pi)$ :

$$v_{b_i}(\pi) = \lambda_{b_i} \left[ \sum_{j=1}^n w_j^{b_i} u_{b_i}(\pi_j) \right] \times \prod_{j=1}^n H(\pi_j) \quad (4.7)$$

Equation 4.7 has two main parts. The first part of the equation is an additive multi-attribute utility function of the type defined in Equation 4.6, which determines the contribution of each of the attributes of  $\pi$ , weighted by their importance according to  $w_j^{b_i}$ . Because it is assumed that all attribute-levels lie on the range  $[0, 1]$ , and that  $\sum_{w \in w^{b_i}} w = 1$ , the conjoint utility of a resource  $\pi$  is naturally scaled between zero and one. It is assumed the utility of a resource to a buyer monotonically increases with the level of its attributes, implying that the weighted attribute utilities of the most desirable resource sums to one. It is also assumed that a buyer would be *indifferent* between an amount of money equal to its budget constraint,  $\lambda_{b_i}$ , and the most desirable resource. Thus, by scaling the

#### 4.2. DECISION MAKING MODELS FOR AGENTS

utility of a resource by  $\lambda_{b_i}$ , a buyer can state its valuation in terms of money.

The second part of Equation 4.7 ensures that a resource  $\pi$ 's utility collapses to zero if any attributes fail to satisfy minimum constraints, regardless of the other attribute utilities. This is achieved by checking every attribute satisfies its minimum constraint using a Heaviside step function:

$$H_{b_i}(\pi_j) = \begin{cases} 1 & \text{if } \pi_j \geq r_{\lfloor j}^{b_i} \\ 0 & \text{otherwise,} \end{cases} \quad (4.8)$$

where  $r_{\lfloor j}^{b_i}$  is buyer  $b_i$ 's minimum constraint for the  $j^{\text{th}}$  attribute. The utility contribution of each individual attribute is calculated according to  $b_i$ 's attribute utility function  $u_{b_i}(\pi_j)$ .

$$u_{b_i}(\pi_j) = \begin{cases} \pi_j & \text{if } r_{\lfloor j}^{b_i} \leq \pi_j \leq r_{\lceil j}^{b_i} \\ r_{\lceil j}^{b_i} & \text{if } \pi_j > r_{\lceil j}^{b_i} \\ 0 & \text{if } \pi_j < r_{\lfloor j}^{b_i} \end{cases} \quad (4.9)$$

$r_{\lfloor j}^{b_i}$  refers to  $b_i$ 's minimum constraint for attribute  $j$ , and  $r_{\lceil j}^{b_i}$  refers to the maximum constraint.  $u_{b_i}(\pi_j)$  ensures that if an attribute has a level in excess of a  $b_i$ 's maximum constraint, it contributes no more utility than if  $\pi_j = r_{\lceil j}^{b_i}$ .

Sellers, being resource providers rather than consumers, are modelled slightly differently to buyers. Each resource type  $\pi$  involves a *cost of production*, defined by a seller's cost function:

$$c_{s_j}(\pi) = \lambda_{s_j} \sum_{i=1}^n w_i^{s_j} u_{s_j}(\pi_i), \quad (4.10)$$

where  $u_{s_j}(\pi_i)$  is the cost contribution of each of the attributes of  $\pi$ , weighted by their relative costs according to  $w_i^{s_j}$ ; given two attributes  $x$  and  $y$ , if  $w_x^{s_j} > w_y^{s_j}$  then it costs more to produce a given increase in attribute  $x$  than it does in attribute  $y$ .

The attribute cost function  $u_{s_j}(\pi_i)$  is defined as follows:

$$u_{s_j}(\pi_i) = \begin{cases} \infty & \text{if } \pi_i > r_{|i}^{s_j} \\ \pi_i & \text{otherwise} \end{cases} \quad (4.11)$$

Thus, a seller is unable to provide a resource with attributes that exceed its maximum production constraint. In all other cases, the cost of production increases linearly with the attribute level.

### Transaction payoffs

Within a double auction environment, the profit or payoff a buyer or seller gains from a transaction is dependent on the type of resource  $\pi$  exchanged, the amount of money  $\tau$  exchanged (transaction price), and any associated market-exchange costs determined by the market-exchange, which will be communicated to each trader as a vector of costs  $\mathbf{c}$ . When a transaction takes place, the buyer  $b_i$ 's payoff  $P_{b_i}$  is:

$$P_{b_i}(\pi, \tau, \mathbf{c}) = v_{b_i}(\pi) - \tau - \sum_{c \in \mathbf{c}} c, \quad (4.12)$$

while for a seller  $s_j$ :

$$P_{s_j}(\pi, \tau, \mathbf{c}) = \tau - c_{s_j}(\pi) - \sum_{c \in \mathbf{c}} c \quad (4.13)$$

In both cases, because agents are assumed to be able to express all their preferences via money, the size of the payoff is equivalent to an equally sized increase in utility.

### 4.2.2 Market-exchange payoff function

Market-exchanges, as with trading agents, are considered utility-maximisers within this model. A market-exchange's utility is measured according to the revenue generated from charging fees to traders, which, as discussed in Section 4.1.1, potentially include registration-based fees and transaction-based

## 4.2. DECISION MAKING MODELS FOR AGENTS

fees. Each market-exchange  $m_k$  maintains an *exchange member* set  $\mathcal{E}_{m_k} \subset \mathcal{T}$ , containing the traders that have joined its market at the beginning of that trading day. During each trading day,  $m_k$  also stores all of the transactions  $\theta$  that it executes, maintaining a transaction set  $\Theta_{m_k}$ , containing all the transactions that took place that day. An exchange's daily profit  $P_{m_k}$  is determined both by the amount of traders that entered the market, and the transactions that the exchange executed:

$$P_{m_k}(\mathcal{E}_{m_k}, \Theta_{m_k}) = |\mathcal{E}_{m_k}| \cdot \zeta_{reg}^{m_k} + \sum_{\theta \in \Theta_{m_k}} 2 \cdot \theta_\tau \cdot \zeta_{tra}^{m_k} + [\theta_{bid} - \theta_{ask}] \cdot \zeta_{com}^{m_k}, \quad (4.14)$$

where  $\zeta_{reg}^{m_k} \in \mathbb{R}_{\geq 0}$ ,  $\zeta_{tra}^{m_k} \in [0, 1]$  and  $\zeta_{com}^{m_k} \in [0, 1]$  refer to  $m_k$ 's *registration fee*, *transaction price fee* and *spread commission fee* levels respectively. Registration fee revenue depends on the number of traders that joined  $m_k$ 's market that day. Both the buyer and seller pay a transaction price fee to  $m_k$ , based upon the transaction price  $\theta_\tau$ . Finally, the spread commission fee is based on the difference between the buyer's bid  $\theta_{bid}$ , and the seller's ask  $\theta_{ask}$ . From Equation 4.14 the reader will note that there are no costs associated with running a market. This is an intentional choice to simplify analysis in future chapters; costs could be added to Equation 4.14 to rectify this in future work.

### 4.2.3 Resource allocation payoff examples

In this section, several visualisations are provided to help the reader understand the impact that traders' preferences and constraints have upon the outcomes of transactions, in terms of buyer valuations, seller costs, and the total utility over both traders. The main purpose of this section is to emphasise that a trader's optimal trading partner (from their perspective and from a social welfare perspective) depends not only on price, but also on the attribute-levels of the resource being traded—a pair of traders could trade many different resource types with each other. Given the multi-attribute nature of the resources defined in



Section 4.1, maximising utility over both a buyer and seller involves consideration of the optimal levels for each resource attribute. For these examples, it is assumed resources have two attributes, which allows visualisation of the effect of changes to their levels.

### The simplest of interactions

In the simplest of cases there exists a buyer  $b_i$  and a seller  $s_j$  who don't have preferences over the two attributes:

$$\mathbf{w}^{b_i} = \langle 0.5, 0.5 \rangle$$
$$\mathbf{w}^{s_j} = \langle 0.5, 0.5 \rangle,$$

that is, the buyer values no attribute higher than any other, and the each attribute is equally expensive to produce more of for the seller. Sellers are assumed to have no minimum constraints on production. Let us assume that the buyer is interested in all but the lowest quality of resource; both vectors of minimum constraints are therefore:

$$\mathbf{r}_{\downarrow}^{b_i} = \langle 0.2, 0.2 \rangle$$
$$\mathbf{r}_{\downarrow}^{s_j} = \langle 0, 0 \rangle$$

Next, assume that neither trader have maximum constraints on the attributes:

$$\mathbf{r}_{\uparrow}^{b_i} = \langle 1.0, 1.0 \rangle$$
$$\mathbf{r}_{\uparrow}^{s_j} = \langle 1.0, 1.0 \rangle$$

#### 4.2. DECISION MAKING MODELS FOR AGENTS

Finally, the traders need a budget constraint, in the form of a limit price  $\lambda$ :

$$\lambda_{b_i} = 20.0$$

$$\lambda_{s_j} = 10.0,$$

where the seller's limit price, which reflects its production cost for a given resource, is less than the buyer's. Because the traders have no preferences over attributes, they are able to trade with each other under two conditions: (i) the buyer's budget is bigger than the seller's, i.e.,  $\lambda_{b_i} \geq \lambda_{s_j}$ ; and (ii) the resource attributes all have levels that exceed the buyer's minimum constraints. By running various resource types  $\pi$  through both the buyer's valuation function  $v_{b_i}(\pi)$ , and the seller's cost function  $c_{s_j}(\pi)$ , it is possible, as shown in Figure 4.1, to visualise how valuations and costs change for different resource types. Further, as shown in Figure 4.1c, it is possible to see the total utility surplus  $u_{b_i,s_j}(\pi)$  of any given transaction over a particular resource. The total utility measure is determined as follows:

$$\begin{aligned} u_{b_i,s_j}(\pi) &= v_{b_i}(\pi) - \tau + \tau - v_{s_j}(\pi) \\ &= v_{b_i}(\pi) - v_{s_j}(\pi) \end{aligned} \tag{4.15}$$

For the sake of simplicity at this stage, potential market-exchanges fees are ignored. In this example, Figure 4.1c shows that the total utility of a transaction would be maximised if the two traders exchanged a resource  $\pi = \langle 1.0, 1.0 \rangle$ . Further, feasible exchange is entirely dependent on the limit prices of the traders; if the limit price of the seller is greater than that of the buyer, no trade could take place over any type of resource.

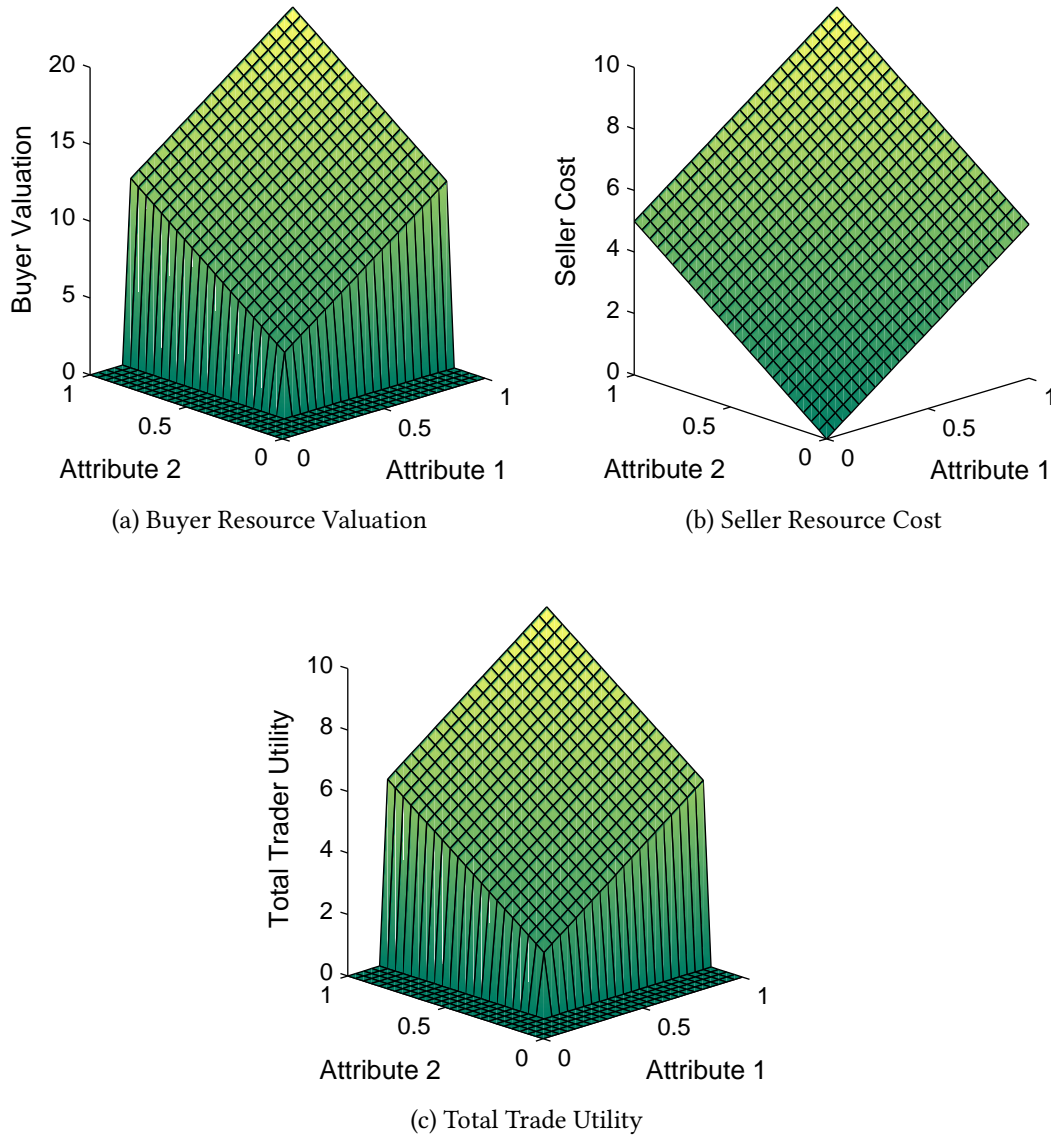


Figure 4.1: Each different point on the on the  $x$  and  $y$  axis describes a resource  $\pi = \langle x, y \rangle$  with the respective attribute-levels. (a) The  $z$  axis describes the buyer's valuation of the resource described by the two attributes; note that for resources with levels less than the buyer's minimum constraint, the resource has zero value. (b) The seller has no minimum production constraints so the cost of producing the resource increases as the levels of the attributes do. (c) The total utility of a transaction between the buyer and seller. Any point that has a non-zero utility would be a mutually beneficial trade; the trade with the highest utility would be for a resource  $\pi = \langle 1.0, 1.0 \rangle$ . The exact utility each trader received would depend on the transaction price, which would lie between the buyer's valuation and the seller's cost.

#### 4.2. DECISION MAKING MODELS FOR AGENTS

##### Buyers with maximum constraints

In this example, a buyer with maximum attribute constraints lower than those of the seller is considered. Again, consider that neither trader has preferences over the two attributes:

$$\mathbf{w}^{b_i} = \langle 0.5, 0.5 \rangle$$
$$\mathbf{w}^{s_j} = \langle 0.5, 0.5 \rangle,$$

Further, let us assume that the traders have the same minimum constraints as the last example:

$$\mathbf{r}_\perp^{b_i} = \langle 0.2, 0.2 \rangle$$
$$\mathbf{r}_\perp^{s_j} = \langle 0.0, 0.0 \rangle$$

Also, let us assume that while the seller is able to produce resources with attributes up to the maximum level, the buyer only requires a resource with a constrained attribute level, e.g.:

$$\mathbf{r}_\perp^{b_i} = \langle 0.5, 0.5 \rangle$$
$$\mathbf{r}_\perp^{s_j} = \langle 1.0, 1.0 \rangle$$

Finally, let us again assume the following budget constraints:

$$\lambda_{b_i} = 20.0$$
$$\lambda_{s_j} = 10.0$$

Having constraints on the maximum desirable attribute levels for a resource has a considerable impact of the buyer's valuation, as shown in Figure 4.2. Because the seller used in the previous example is also used here, the seller's cost function is

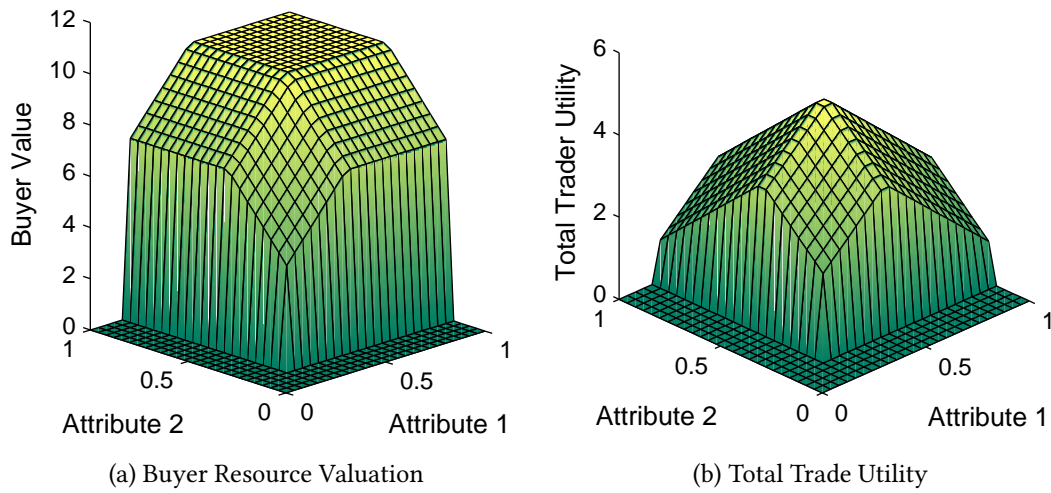


Figure 4.2: Each different point on the on the  $x$  and  $y$  axis describes a resource  $\pi = \langle x, y \rangle$  with the respective attribute-levels. In this example the seller is identical to that in Figure 4.1b. (a) The  $z$  axis describes the valuation of the different resource types for a buyer with maximum constraints  $\mathbf{r}_i^{b_i} = \langle 0.5, 0.5 \rangle$ . Due to these maximum constraints, the buyer's valuation does not increase for resources with attribute levels beyond its maximum constraints. (b) The total utility of a transaction between the buyer and the seller shown in Figure 4.1b. Any point that has a non-zero utility would be a mutually beneficial trade. While any resource with attribute-levels beyond the buyer's maximum constraints would not be valued higher, it would cost more for the seller to produce. Therefore, the trade that maximises the total utility is for a resource  $\pi = \langle 0.5, 0.5 \rangle$ .

#### 4.2. DECISION MAKING MODELS FOR AGENTS

the same as that shown in Figure 4.1b. The immediate difference between this and the previous simpler case, where the buyer had no maximum constraints, is that the resource that maximises the total utility over the trade is no longer the one with maximum values for attributes; instead, the resource type maximising utility is  $\pi = \langle 0.5, 0.5 \rangle$ , which in this case aligns with the buyers maximum constraints. Of course, a marketplace trying to decide on the type of resource to be traded within its market would be unaware of these constraints *a priori*.

##### Traders with preferences over attributes

The final example to be shown involves looking at a buyer and seller that have preferences over the two resource attributes:

$$\mathbf{w}^{b_i} = \langle 0.9, 0.1 \rangle$$

$$\mathbf{w}^{s_j} = \langle 0.1, 0.9 \rangle$$

In this case, the buyer strongly prefers attribute one to attribute two, meaning that it is willing to apportion more of its budget to that resource than the other. The seller can produce a given increase of attribute one for less than it can produce the same increase in attribute two, i.e., attribute one is more expensive for the seller to produce. Let us maintain the same minimum constraints on the traders as the previous examples:

$$\mathbf{r}_{\downarrow}^{b_i} = \langle 0.2, 0.2 \rangle$$

$$\mathbf{r}_{\downarrow}^{s_j} = \langle 0, 0 \rangle$$

To simplify this analysis, let us remove the previous buyer's maximum constraint:

$$\mathbf{r}_{\uparrow}^{b_i} = \langle 1.0, 1.0 \rangle$$

$$\mathbf{r}_{\uparrow}^{s_j} = \langle 1.0, 1.0 \rangle$$

Finally, in order to highlight the impact that preferences have on feasible trades, let us again assume the following budget constraints:

$$\lambda_{b_i} = 20.0$$

$$\lambda_{s_j} = 25.0,$$

that is to say, the *seller's* budget constraint is bigger than the buyer's. In the absence of preferences, if  $\lambda_{s_j} > \lambda_{b_i}$  then a trade can never take place, because the seller's costs will always be larger than the buyer's valuations. However, as shown in Figure 4.3, when a buyer values some attributes more than others, and a seller is able to produce some attributes cheaper than others, it is possible for mutually beneficial trades to take place over some resource types.

By following these examples, and considering large populations of traders with potentially different preferences and constraints, it should become clear that the market-exchanges' task of choosing the resource type to be traded within their markets is non-trivial, given that underlying trader preferences and constraints can't be known *a priori*; strategies for tackling this challenge are the subject of Chapter 5.

### 4.3 Market-exchange Agent Mechanics

Market-exchange agents operating within this resource allocation approach involve two main mechanisms: (i) a double action mechanism, which allows the agent to run a double auction for allocating resources between buyers and sellers; and (ii) a mechanism for deciding what type of resource will be traded within its market each trading day. Section 4.2.2 described how market-exchanges are assumed to be self-interested agents, attempting to maximise revenue generated from charges and fees levied on traders within their market. The type of resource traded within their market will affect the market-exchange's profitability, and as

### 4.3. MARKET-EXCHANGE AGENT MECHANICS

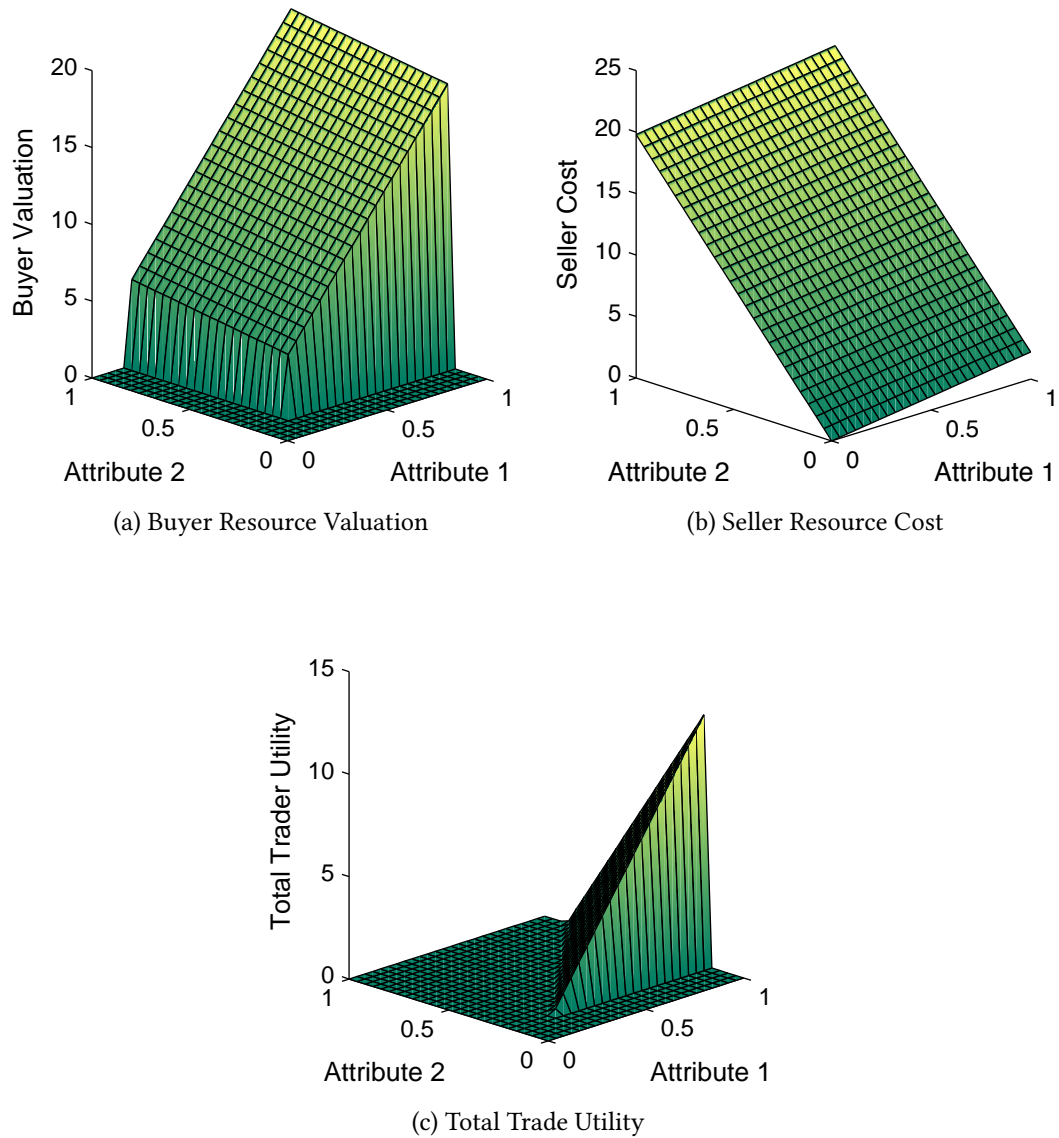


Figure 4.3: Each different point on the on the  $x$  and  $y$  axis describes a resource  $\pi = \langle x, y \rangle$  with the respective attribute-levels. (a) the buyer's valuation increases linearly as the attribute levels of the resource increase, however, a strong preference for attribute one has rotated the valuation landscape, such that valuation increases more dramatically for an increase in attribute one. (b) the seller's cost increases more slowly with an increase in attribute one than with attribute two. (c) Total utility of a transaction between the buyer and seller. Because of a higher seller budget constraint the seller's cost  $c_s(\langle 1.0, 1.0 \rangle) = 25$  is bigger than the buyer's valuation  $v_{b_i}(\langle 1.0, 1.0 \rangle) = 20$ . However, a mutually beneficial trade can take place over resources with certain attributes; the total utility is maximised for the resource type  $\pi = \langle 1.0, 0.2 \rangle$ .



the previous section has demonstrated, selecting the attribute levels that optimise the total utility over a transaction—which should in turn optimise the potential revenue from such a transaction—is not always straightforward.

The method by which a market-exchange decides on the attribute-levels of the type of resource to be traded within its market is determined by its *attribute-level selection strategy*, and based upon the previous section it should be clear that this is a challenging problem. Chapter 5 will be dealing with the design and analysis of appropriate attribute-level selection strategies for the allocation of multi-attribute computational resources.

### 4.3.1 Double auction policies

This thesis does not concern itself with the design and analysis of policies or rules pertaining to the running of a double auction *per se*. As such, several previously well-defined double auction policies are used to run market-exchange's double auction mechanisms throughout this thesis. The various double auction policies used by market-exchanges are as follows.

#### Charging policy

At the beginning of this chapter the main assumed types of charges were outlined. A double auction charging policy essentially outlines these charges, and specifies under what conditions traders are subjected to them. Within this thesis, it is assumed that these charges remain stationary for the duration of a simulation, i.e., they do not dynamically change over time in response to any environmental conditions. Exploration of the relative merits for using dynamic charging policies when allocating these types of multi-attribute resources is saved for future work.

#### Clearing policy

As discussed in Chapter 2, a continuous double auction auction mechanism might be more appropriate than a clearing house variant for scenarios where supply

### 4.3. MARKET-EXCHANGE AGENT MECHANICS

and demand could shift rapidly, or where it might not be practical for traders to wait for the market to clear. As such, all market-exchanges within this model use continuous double auction (CDA) mechanisms. From an implementation point of view, each market-exchange uses the *4-Heap* algorithm [185] to maintain uncleared bids and asks in their market, using appropriate data structures.

#### Matching policy

The matching policy perhaps most commonly used in double auction environments is the *market equilibrium* matching policy [104]. Within a clearing house auction, market equilibrium involves clearing the market at the reported supply and demand levels [117], yet these are not available in a CDA auction, so traders are simply matched as soon as a bid and ask are compatible; if there are multiple compatible offers they are prioritised according to time of submission.

#### Pricing policy

The pricing policy specifies the transaction price at which a trade takes place, given a matching bid and ask. A discriminatory *k-pricing* policy [150, 8] calculates the transaction price using a parameter  $\kappa \in [0, 1]$ . For a transaction  $\theta$ , containing the bid and ask prices  $\theta_{bid}$  and  $\theta_{ask}$ , market-exchange  $m_k$  determines the transaction price  $\theta_\tau$  as follows:

$$\theta_\tau = \theta_{bid} \times \kappa_{m_k} + \theta_{ask} \times (1 - \kappa_{m_k}) \quad (4.16)$$

The setting of  $\kappa_{m_k}$  determines how favourable the transaction price is to the buyer and seller: when  $\kappa_{m_k} = 0$  ( $\kappa_{m_k} = 1$ ) the transaction price is unilaterally set according to the value of the ask (bid). The value of  $\kappa_{m_k}$  can affect how attractive the market is to either buyers or sellers, thus is it typical to set  $\kappa_{m_k} = 0.5$  when it is desirable not to bias transaction prices towards buyers or sellers. Within this thesis, all market-exchanges use  $\kappa_{m_k} = 0.5$ .

### Quoting policy

The quoting policy determines what information is given to traders in terms of the current prices within the market. All market-exchanges within this model use *two-sided* quoting [117], which publicly states the current highest unmatched bid and lowest unmatched ask to all traders within the market; these prices are updated dynamically as new offers enter the market, or trades executed.

### Shout accepting policy

The shout accepting policy specifies under what conditions offers shouted by traders are accepted into the market, by the market-exchange agent. In the most basic configuration, any shout is accepted into the market; however, it is often more appropriate for a market-exchange to impose some limits on the shouts accepted, to encourage a more efficient market, and reduce excess computational work. One shout accepting policy that encourages convergence towards the competitive market equilibrium is the *beat the quote* shout accepting policy [186]. Also known as the *NYSE rule*, due its use on the New York Stock Exchange [113], the policy states that only shouts that improve upon the current quote prices, i.e., bids (asks) that are  $\geq$  ( $\leq$ ) than the highest (lowest) unmatched bid (ask), are accepted into the market.

## 4.4 Trading Agent Mechanics

In this section, the main mechanisms used by the trading agents within this model are defined and discussed. Trading-agents are composed of two main parts [23]: (i) a *trading strategy* that dictates at what price the buyer or seller shouts offers into the market; and (ii) a *market-selection strategy* that dictates at which market to enter each trading day. The rest of this section outlines the strategies used, and how they are adapted for use in this multi-market approach to resource allocation.

#### 4.4.1 The Zero-Intelligence Plus trading strategy

Throughout this thesis, it is assumed that all trading agents will be using Cliff's [34] *Zero Intelligence Plus* (ZIP) trading strategy. The two main reasons for this choice are: (i) the ZIP strategy has been extensively analysed in double auction settings [34, 39, 17], and ZIP traders have been shown capable of achieving efficient allocations [34]; and (ii) the ZIP trading strategy is relatively simple computationally, and thus scales well for use in many large-scale experiments. As discussed in Section 2.3.2 on Page 30, ZIP agents possess the minimal intelligence for converging, under a wide range of supply and demand schedules, on a market's competitive equilibrium price.

The ZIP algorithm has two main parts. The first is a deterministic algorithm that decides which direction (if at all) the agent should adjust its current *shout price*. The second part is a machine learning technique that decides by what amount to change their shout price; the machine learning technique works as follows. Importantly, a ZIP trader, being rational, will never shout an offer into the market that exceeds its valuation (if a buyer) or cost (if a seller) of the type of resource being traded in the market. Thus, each trading period  $t$  a ZIP trader  $a_i$  calculates its shout price  $\rho_{a_i}^t$  by scaling its valuation  $v_{a_i}$  by a *profit-margin*  $\mu_{a_i}^t$ :

$$\rho_{a_i}^t = v_{a_i} \times [1 + \mu_{a_i}^t], \quad (4.17)$$

where,

$$v_{a_i} = \begin{cases} v_{b_i}(\boldsymbol{\pi}) & \text{if } a_i \in \mathcal{B} \\ c_{s_i}(\boldsymbol{\pi}) & \text{if } a_i \in \mathcal{S} \end{cases}$$

Depending on whether the trader is a buyer or seller,  $v_{a_i}$  is set as the valuation or cost of the resource being traded within the market. Given buyers and sellers make more profit when their transaction prices are lower and higher respectively, a buyer's *profit margin* is increased when it decreases  $\mu_{a_i}^t$  and a seller's when it

increases  $\mu_{a_i}^t$ . Margins must be non-negative for sellers, i.e.,  $\forall_{a_i \in \mathcal{S}}, \mu_{a_i}^t \in [0, \infty]$ , demonstrating that it is possible for sellers to ask any amount for their resource, but cannot go below their valuation  $v_{a_i}$ . Buyers' margins must lie within the range  $\forall_{a_i \in \mathcal{B}}, \mu_{a_i}^t \in [-1, 0]$ ; they cannot shout more than their valuation, but they clearly can't shout a negative price either.

When an offer is shouted, it may be accepted by the market-exchange, and may result in a transaction. These outcomes influence how the profit margin, and thus shout price, is adapted for the next trading period. Using the Widrow-Hoff Delta Rule [179], the profit margin  $\mu_{a_i}^{t+1}$  is set by rearranging Equation 4.17 in terms of  $\mu_{a_i}^t$  and then applying an update value  $\Delta_{a_i}^t$ , known as the *Widrow-Hoff delta value*:

$$\mu_{a_i}^{t+1} = \frac{\rho_{a_i}^t + \Delta_{a_i}^t}{v_{a_i} - 1} \quad (4.18)$$

The Widrow-Hoff delta value  $\Delta_{a_i}^t$  aims to move a trader's shout price towards a *target price*  $T_{a_i}$ , which is determined every trading day, and depends upon information the trader has gleaned from the market.

$$\Delta_{a_i}^t = \beta_{a_i} \times [\tau_{a_i}^t - \rho_{a_i}^t], \quad (4.19)$$

where  $\beta_{a_i}$  is trader  $a_i$ 's *learning rate*, which dictates how quickly  $\rho_{a_i}$  converges towards the target  $T_{a_i}$ . The target price  $T_{a_i}$  is an elegant feature of the ZIP algorithm. Cliff realised that while intuitively it would make sense to set  $T_{a_i}^t$  to last price shouted in the market  $q^t$ , if  $\rho_{a_i}^t \simeq q^t$  there would be little change in a trader's shout, and that "...there is a need for the agents to be constantly testing the market, always pushing for higher margins." [33, p. 44.]. Therefore,  $T_{a_i}^t$  is set by randomly perturbing the last shouted price in the market (perhaps representative of the real-world differences that traders have in their pricing strategies).

$$T_{a_i}^t = U_{a_i}^t \cdot q^t + \widehat{U}_{a_i}^t \quad (4.20)$$

#### 4.4. TRADING AGENT MECHANICS

Parameter	Raise Price	Lower Price
$U_{min,a_i}$	1	$1 - u_{a_i}$
$U_{max,a_i}$	$1 + u_{a_i}$	1
$\hat{U}_{min,a_i}$	0	$-\hat{u}_{a_i}$
$\hat{U}_{max,a_i}$	$\hat{u}_{a_i}$	0

Table 4.1: In the ZIP algorithm, the bounds for uniform distributions are adjusted according to whether the algorithm wishes to raise or lower its shout price.  $u_{a_i} \in [0, 1]$  and  $\hat{u}_{a_i} \in [0, 1]$  are free parameters that agent  $a_i$  would need to set.

Two types of perturbations are applied to  $q^t$ : the first,  $U_{a_i}^t \in [U_{min,a_i}, U_{max,a_i}]$ , scales  $q^t$  across a uniform distribution; the second,  $\hat{U}_{a_i}^t \in [\hat{U}_{min,a_i}, \hat{U}_{max,a_i}]$ , is an absolute perturbation.

Finally, ZIP uses *momentum* [69, p. 71] to *dampen* noise in  $\Delta_{a_i}^t$ , which may arise due to the dynamic nature of shouts in the market, and thus target prices. Rather than using  $\Delta_{a_i}^t$  directly, a momentum coefficient  $\gamma_{a_i}$  is applied, and a new update rule  $\Gamma_{a_i}$  is used instead of the  $\Delta_{a_i}$  defined in Equation 4.19.

$$\Gamma_{a_i}^{t+1} = \gamma_{a_i} \Gamma_{a_i}^t + [1 - \gamma_{a_i}] \Delta_{a_i}^t \quad (4.21)$$

Because  $\Gamma_{a_i}$  is used instead of  $\Delta_{a_i}$ , Equation 4.18 is replaced by Equation 4.22.

$$\mu_{a_i}^{t+1} = \frac{\rho_{a_i}^t + \Gamma_{a_i}^t}{v_{a_i} - 1} \quad (4.22)$$

That concludes the machine learning techniques used to adapt a ZIP agent's shout price. In Algorithm 4.1, the deterministic rules that dictate the *direction* in which a ZIP agent adjusts its shout price, is shown. In order to know which direction to adjust its price in, a ZIP trader needs only to know the last shouted price  $q$  in the market, whether that shout was accepted in to the market, and whether the shout was a bid or an offer. Based upon that information, a ZIP trader either raises or lowers its shout price, by adjusting the bounds of the uniform distributions that  $U_{a_i}^t$  and  $\hat{U}_{a_i}^t$  are drawn from in Equation 4.20. How these bounds are adjusted for trader  $a_i$  are shown in Table 4.1. For all simulation studies within this thesis, parameters for traders using the ZIP algorithm were set similarly to Cliff and

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**Algorithm 4.1** The ZIP algorithm

---

```
1: if  $a_i \in \mathcal{S}$  then {Trader is a seller.}
2:   if last shout in market accepted at price  $q$  then
3:     if  $\rho_{a_i}(t) \leq q(t)$  then
4:       increase profit margin (raise price).
5:     end if
6:     if last shout in market was a bid and  $\rho_{a_i} \geq q$  and active then
7:       decrease profit margin (lower price).
8:     end if
9:   else
10:    if last shout was an offer and  $\rho_{a_i} \geq q$  and active then
11:      decrease profit margin (lower price).
12:    end if
13:  end if
14: else {Trader is a buyer.}
15:   if last shout in market accepted at price  $q$  then
16:     if  $\rho_{a_i} \geq q$  then
17:       increase profit margin (lower price).
18:     end if
19:     if last shout in market was a offer and  $\rho_{a_i} \leq q$  and active then
20:       decrease profit margin (raise price).
21:     end if
22:   else
23:     if last shout was a bid and  $\rho_{a_i} \leq q$  and active then
24:       decrease profit margin (raise price).
25:     end if
26:   end if
27: end if
```

---

#### 4.4. TRADING AGENT MECHANICS

Bruten's [34] original simulation studies. Specifically:

$$\begin{aligned}\forall_{a_i \in \mathcal{T}} \quad & \beta_{a_i} \in [0.1, 0.2] \\ & \gamma_{a_i} \in [0.05, 0.35] \\ & \mathbf{u}_{a_i} = 0.05 \\ & \widehat{\mathbf{u}}_{a_i} = 0.05\end{aligned}$$

and additionally:

$$\begin{aligned}\forall_{a_i \in \mathcal{B}} \quad & \mu_{a_i}^0 \in [-0.35, -0.05] \\ \forall_{a_i \in \mathcal{S}} \quad & \mu_{a_i}^0 \in [0.05, 0.35]\end{aligned}\tag{4.23}$$

where for all parameter ranges, the value is drawn from a Uniform distribution bounded by the range at the beginning of the simulation;  $\mu_{a_i}^0$  refers only to the initial profit margin at time  $t = 0$ .

#### 4.4.2 Integrating market fees

Recall that traders using the ZIP algorithm never shout offers in excess of their valuations (buyers) or costs (sellers) of the resource type being traded in the market. However, given that, as described in Section 4.1.1, there are several possible charges for joining and trading within a market, it is possible that a trader may still trade at a loss, even if their offer does not exceed their valuation or cost. Typically, in the literature referring to deploying ZIP in a single market situation, charges are not normally of importance in the research being carried out, thus they are not explicitly considered. However, in a multi-market situation, charges affect traders' preferences over market-selection, thus they need to be factored into ZIP's shouting algorithm. Thus, market-exchange charges are integrated into a trader's valuation. In the case of a trader that is a buyer, i.e.,  $a_i \in \mathcal{B}$ , rather than the ZIP algorithm using  $v_{a_i} = v_{b_i}(\boldsymbol{\pi})$ , it uses  $v_{a_i} = \widehat{v}_{b_i}(\boldsymbol{\pi})$ ,



where:

$$\widehat{v}_{b_i}(\boldsymbol{\pi}) = [v_{b_i}(\boldsymbol{\pi}) - \zeta_{m_k}^{reg}] \times [1 + \zeta_{m_k}^{tra}]^{-1} \quad (4.24)$$

First the buyer decreases its resource valuation  $v_{b_i}(\boldsymbol{\pi})$  by market-exchange  $m_k$ 's registration fee  $\zeta_{m_k}^{reg}$ . Secondly, it considers the transaction price fee it would have to pay if it traded at its *discounted* valuation, and adjusts for it by using the multiplicative inverse of  $1 + \zeta_{m_k}^{tra}$ . Thus, if the buyer were to transact at  $\widehat{v}_{b_i}$ , then the price the buyer paid, including all applicable charges would be equal to its initial valuation  $v_{b_i}(\boldsymbol{\pi})$ . For a seller  $a_j \in \mathcal{S}$  using the ZIP algorithm,  $v_{a_j} = c_{s_j}(\boldsymbol{\pi})$  becomes  $v_j = \widehat{c}_{s_j}$ ; sellers need to *increase* their costs rather than discount them:

$$\widehat{v}_{s_j} = [v_{s_j}(\boldsymbol{\pi}) + \zeta_{m_k}^{reg}] \times [1 - \zeta_{m_k}^{tra}]^{-1} \quad (4.25)$$

These mechanisms ensure that, as long as traders trade resources with the attribute-level specified by the market-exchange  $m_k$ , they will never make a loss from successfully transacting within a market-exchange.

### 4.4.3 Market-selection strategy

Market-exchanges have the ability to dynamically set and vary the attribute-levels of the resource types to be traded within their markets.

Section 4.2.3 demonstrated that trader preferences and constraints affect the desirability of different resource types. Therefore, an important aspect of a trading agent is the mechanism by which it *chooses* which market-exchange, and thus resource market, to join each trading day.

#### A consumer theoretic approach to market selection

Modern consumer theory supposes that resource-constrained consumers, being rational and time-constrained (and processing-power-constrained and memory-constrained), only consider a subset of all options available [143, 88]. Some options are immediately rejected without detailed consideration, because

#### 4.4. TRADING AGENT MECHANICS

they have below-threshold values on essential attributes (so-called *inept* or unacceptable options [112]). Only the contents of these subsets, termed *consideration sets* [144], are then carefully deliberated over, before ultimately one option is chosen. The options that do not score highly enough to be chosen in this evaluation are called *inert* options [112].

In the same spirit, the decision-making models used by traders within this model take a consumer marketing model approach [94]. A trader's *market-selection strategy* is designed such that it only considers a subset of available markets each trading day, by forming a consideration set  $\mathcal{C}$  of market-exchanges. Market-exchanges are excluded from a trader's consideration set if the resource type being traded within its market is considered *inept* by the trader. Buyers consider resources to be inept if one of the attribute-levels fails to meet its minimum constraint, while sellers consider resources inept if one of the attribute-levels is beyond their production ability, i.e., maximum constraints. Thus, for a buyer  $b_i$ :

$$\mathcal{C}_{b_i} = \{m_k \in \mathcal{M} : (\forall \pi_j \in \boldsymbol{\pi})(\pi_j \geq r_{|j}^{b_i})\} \quad (4.26)$$

where  $r_{|j}^{b_i}$  is  $b_i$ 's minimum constraint for the  $j^{\text{th}}$  attribute of the resource  $\boldsymbol{\pi}$  specified by market exchange  $m_k$ . And, for a seller  $s_j$ , its consideration set,  $\mathcal{C}_{s_j}$ , is formed as follows:

$$\mathcal{C}_{s_j} = \{m_k \in \mathcal{M} : (\forall \pi_j \in \boldsymbol{\pi})(\pi_j \leq r_{|j}^{s_j})\} \quad (4.27)$$

Equations 4.26–4.27 ensure no buyer enters a market where the resources on offer do not satisfy its minimum constraints, and that no seller will enter an exchange where it would have to produce resources beyond its production capabilities.

### Market selection

Once a consideration set is formed, more careful evaluation can be made for market-selection. It is possible for a trader to successfully trade over every resource type defined by each of the market-exchanges within the consideration set, however: (i) each market-exchange will potentially have different charges and fees; and (ii) each market will have differing numbers of traders within it, and different supply and demand schedules. Thus, the problem a trader faces in the presence of competing market-exchanges is that of *exploitation* versus *exploration*. Choosing markets from the consideration set is a similar problem to that faced by traders in other domains, e.g, traders within the CAT tournament must choose between all competitions' entrants. Leveraging those strategies [118], the problem of market-selection within the consideration set is treated as an *n-armed bandit problem*. One of the simplest n-armed strategies, the  $\epsilon$ -greedy strategy [164], is used by traders in the CAT tournaments [24]. Each trader  $a_i$  using the strategy maintains a vector of *reward* values  $\mathbf{R}^{a_i}$ :

$$\mathbf{R}^{a_i} = \left\langle R_{m_1}^{a_i}, R_{m_2}^{a_i}, \dots, R_{m_{|\mathcal{M}|}}^{a_i} \right\rangle \quad (4.28)$$

Thus, each market-exchange  $m_k \in \mathcal{M}$  has a reward  $R_{m_k}^{a_i}$  associated with it; initially at time  $t = 0$ ,  $\forall m_k, R_{m_k}^{a_i}(t) = 0$ . If during a trading day  $t$ , a trader  $a_i$  joins a market-exchange  $m_k$ , then at the end of the trading day, it updates its reward value associated with  $m_k$  according to:

$$R_{m_k}^{a_i}(t+1) = R_{m_k}^{a_i}(t) + \delta_{a_i} \cdot [P_{a_i}^t - R_{m_k}^{a_i}(t)], \quad (4.29)$$

where  $P_{a_i}^t$  refers to  $a_i$ 's profit for trading day  $t$ , and  $\delta_{a_i}$  to a discounting factor that  $a_i$  uses to ensure that more recent profits contribute further towards  $R_{m_k}^{a_i}$ , i.e.,  $R_{m_k}^{a_i}$  becomes an *exponential moving average*. In all the simulations within this thesis,  $\delta_{a_i} = 0.1$ , which ensures that older observations are not too aggressively

forgotten.

The  $\varepsilon$ -greedy strategy selects the market-exchange with the highest reward according with probability  $\varepsilon$ , while a random market-exchange is chosen with probability  $1 - \varepsilon$  times. Thus,  $\varepsilon$  represents the probability of exploitation (joining the historically best market-exchange), while  $1 - \varepsilon$  represents the probability of exploration. If no single market-exchange has the highest unique reward, then  $a_i$  chooses randomly between all market-exchanges with the join highest rewards. It is quite common for  $\varepsilon = 0.1$  to empirically yield the best balance between exploration and exploitation [164, pp. 29] in terms of overall performance, and  $\varepsilon = 0.1$  is the setting used for all traders in simulation within this thesis.

## 4.5 An Algorithm for Measuring Allocative Efficiency

One of the metrics of interest when designing and analysing resource allocation mechanisms is the resulting *allocative efficiency*. The market-based system proposed in this chapter considers multiple competing marketplaces hopefully self-organising into market niches that satisfy market segments in a population of traders. While the allocative efficiency within each market is expected to be comparable to that empirically observed by other researchers working with double auctions and ZIP agents [33], the efficiency across the entire system of market-exchanges is of particular interest, because it will give an indication of their abilities to carve out market niches and attract traders. As such, of primary interest is the overall allocative efficiency of the *entire system*.

Recall from Chapter 2 that an allocation, i.e., a set of agents each possessing—in this case—either some cash or a resource, is said to be efficient *iff* the total utility of all agents is *maximised*. In practice, double-auction allocations are often not efficient; therefore, allocative efficiency (*AE*) is typically defined as a measure of how *close* the total utility of an allocation is to the utility that an

efficient allocation would otherwise generate:

$$AE = \frac{U(\Theta)}{U(\Theta^*)}, \quad (4.30)$$

where  $U(\Theta)$  indicates the utility gained from an allocation  $\Theta$ , and  $U(\Theta^*)$  refers to the utility gained from an *efficient allocation*  $\Theta^*$ , which is, in that sense optimal.

#### 4.5.1 Calculating an allocation's utility

The total utility  $U(\Theta)$  gained from an allocation  $\Theta$ , is simply the sum of all individual transaction utilities within each market:

$$U(\Theta) = \sum_{\theta \in \Theta} U(\theta) \quad (4.31)$$

For each transaction  $\theta$ , its utility  $u(\theta)$  is dependent only on the total gain in utility from the buyer and seller trading with each other. While both the buyer and seller may incur registration, transaction or commission fees, which must be paid to the exchange that generated the transaction, the *total* utility of *all* agents involved in a transaction is only dependent on the private valuation of the buyer and cost to the seller involved.

$$\begin{aligned} u(\theta) &= P_{b_i}(\theta_\pi, \theta_\tau, \mathbf{c}_{b_i}) + P_{s_j}(\theta_\pi, \theta_\tau, \mathbf{c}_{s_j}) + \sum_{c \in \mathbf{c}_{b_i} + \mathbf{c}_{s_j}} c \\ &= v_{b_i}(\theta_\pi) - \theta_\tau - \sum_{c \in \mathbf{c}_{b_i}} c + \theta_\tau - c_{s_j}(\theta_\pi) - \sum_{c \in \mathbf{c}_{s_j}} c + \sum_{c \in \mathbf{c}_{b_i} + \mathbf{c}_{s_j}} c \\ &= v_{b_i}(\theta_\pi) - c_{s_j}(\theta_\pi), \end{aligned} \quad (4.32)$$

where:

$$\begin{aligned} b_i &= \theta_b \\ s_j &= \theta_s \\ m_k &= \theta_m, \end{aligned}$$

#### 4.5. AN ALGORITHM FOR MEASURING ALLOCATIVE EFFICIENCY

and  $\sum_{c \in c_{b_i} + c_{s_j}} c$  is the total revenue the market-exchange would receive from the transaction in charges and fees levied on the two traders. Because the overall transaction utility considers both the traders and the exchange, the utility measure reduces down to the difference between the buyer's valuation for the transacted resource  $\theta_\pi$ , and the seller's production cost. Measuring the total utility  $U(\Theta)$  of an allocation is straightforward, but calculating  $U(\Theta^*)$  requires knowledge of an efficient allocation  $\Theta^*$ , which involves solving the following optimisation problem to find the set of optimal transactions  $\theta \in \Theta^*$ .

$$\arg \max_{(\Theta^*)} \sum_{\theta \in \Theta^*} v_{b_i}(\theta_\pi) - c_{s_j}(\theta_\pi), \quad (4.33)$$

where,

$$\begin{aligned} b_i &= \theta_b \\ s_j &= \theta_s \end{aligned}$$

In terms of single-attribute *fungible* resources, which are resources where only *price* influences preferences over them, as Phelps [137, pp. 17–19] notes, the problem is simple to solve. One only need know the private values of both the buyers and sellers in the auction, since there is only one *type* of resource that could be exchanged between each buyer and seller; thus a trader's valuation or cost is always equivalent to its limit price.

$$\begin{aligned} v_{b_i} &= \lambda_{b_i} \\ c_{s_j} &= \lambda_{s_j} \end{aligned}$$

Briefly, to find the optimal allocation for a single-attribute resource case, buyer valuations are first sorted in *descending* order. Let  $\Lambda^b = \{\lambda_{b_1}, \lambda_{b_2}, \dots, \lambda_{b_n}\}$  be the *multi-set* of all buyer valuations where:

$$\forall_{ij} i < j \implies \lambda_{b_i} \geq \lambda_{b_j}$$

Sorting the set of seller valuations in *ascending* order, let  $\Lambda^s = \{\lambda_{s_1}, \lambda_{s_2}, \dots, \lambda_{s_n}\}$  be the *multi-set* of all seller valuations where:

$$\forall_{ij} i < j \implies \lambda_{s_i} \leq \lambda_{s_j}$$

Finally, by iterating through  $\Lambda^b$  and  $\Lambda^s$ , each of the transactions that belong in the optimal transaction set can be indicated by  $\lambda_{b_i} \geq \lambda_{s_j}$ . However, the model developed within this chapter is for complex multi-attribute resources, where optimally allocating a resource from a provider to a consumer involves working out the optimal *type* of resource, as well as assessing cost and value. Thus, the method above defined for solving the optimisation problem in Equation 4.33, cannot be used to find the optimal allocation for an instance of this resource allocation model.

## 4.5.2 The Hungarian Algorithm for assignment problems

The Hungarian Algorithm [90, 110] is a remarkable algorithm for finding solutions to what are classically known as *assignment problems*. According to Burkard et al., assignment problems “. . . deal with the question of how to assign  $n$  items (jobs, students) to  $n$  other items (machines, task).” [21, p. 1], such that some overall payoff (cost) metric is maximised (or minimised), and traditionally were of interest to operations researchers looking to improve the efficiencies or performance of various systems. Assigning members from two sets to each other in an optimal way is identical to the problem faced when determining an optimal allocation of resources between a set of buyers and sellers; more formally:

**Definition 4.1. (Optimal Allocation Problem):** Let  $U$  be a  $\mathcal{B}$ -by- $\mathcal{S}$  utility matrix, and let  $u_{ij} = u(\theta)$  be the total utility from a transaction  $\theta$  between buyer  $i \in \mathcal{B}$  and seller  $j \in \mathcal{S}$ , over some resource  $\pi$ . A set of elements (transactions) in the utility matrix  $U$  are said to be *independent* if no two of them lie on the same row or column. The problem is to choose a set of  $n$  independent transactions from  $U$ , so that the sum of their utilities are maximum.

#### 4.5. AN ALGORITHM FOR MEASURING ALLOCATIVE EFFICIENCY

Informally, buyers and sellers can only take part in at most one transaction, and the aim is to find the set of transactions, i.e., the transaction set  $\Theta^*$ , for which total utility  $U(\Theta^*)$  is maximised. The original Hungarian Algorithm usually expected the matrix size to be  $m$ -by- $m$ , but Munkres [110] provides an implementation of the algorithm for non-square matrices. The algorithm itself is strongly polynomial, with a worst case complexity of  $O(n^3)$ , where  $n = \max(|\mathcal{B}|, |\mathcal{S}|)$ . Gerkey [64] (originally Winston [182]) provides a particularly succinct explanation of how the algorithm progresses:

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**Algorithm 4.2** The Hungarian Algorithm

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(1) Construct the reduced cost matrix by subtracting from each element the minimum element in its row and the minimum element in its column.

(2) Find the minimum number of horizontal and vertical lines required to cover all the zeros in the reduced cost matrix. If  $n$  lines are required, then an optimal assignment is available in the covered zeros. If fewer than  $n$  lines are required, go to Step 3.

(3) Find the smallest nonzero uncovered element in the reduced cost matrix. Subtract that value from each uncovered element of the reduced cost matrix and add it to each twice-covered element in the reduced cost matrix. Go to Step 2.

---

Gerkey [64, pp. 20–21]

A more formal and precise description of the Hungarian Algorithm can be found in Munkres [110].

#### 4.5.3 Multi-attribute resource assignment problems

The Hungarian Algorithm finds a bijection of two sets that maximises (minimises) the overall sum of payoffs (costs) for the matrix formed from the two sets. For solving the *Optimal Allocation Problem* the utility matrix  $U$  needs to be populated with transaction utilities  $u_{ij} = v_{b_i}(\boldsymbol{\pi}) - c_{s_j}(\boldsymbol{\pi})$ . However, this is non-trivial because of the multi-attribute nature of both the buyer and seller's valuation and cost functions. As observed from the trader payoff examples in Section 4.2.3, each



resource type can provide different levels of overall utility when exchanged. Thus, given a population of traders, in order to populate  $\mathbf{U}$  and calculate the optimal allocation, the attribute-levels of the optimum resource that could be traded between each buyer and seller must be determined.

**Definition 4.2. (Optimal Attribute-levels for a Traded Resource Problem):** Given a buyer  $b_i \in \mathcal{B}$  and a seller  $s_j \in \mathcal{S}$ , find the vector of attribute-levels that describe the resource  $\pi$ , that when exchanged between  $b_i$  and  $s_j$  maximises the total utility over  $b_i$  and  $s_j$ .

This problem is equivalent to the following optimisation problem:

$$u_{b_i, s_j}^* = \arg \max_{\pi^*} \{v_{b_i}(\pi^*) - c_{s_j}(\pi^*)\}, \quad (4.34)$$

where  $\pi^*$  is the optimal type of resource that could be exchanged.

### Optimal allocation problem solution

Other multi-attribute or combinatorial optimisation problems [125, 13], which often have complex non-linear dependencies between item attributes from different traders, or over bundles of different items, thus making the problems  $\mathcal{NP}$ . However, because it is assumed agents within this model only have linear dependencies between attribute-levels and valuations (costs), and also that the attributes are *utility independent* of each other, it is possible to use a *greedy* method to calculate a solution to the *optimal attribute-levels for a traded resource problem*. Recall from Equation 4.1, a resource  $\pi$  is made up of a vector of  $n$  attributes:

$$\pi = \langle \pi_1, \pi_2, \dots, \pi_n \rangle,$$

where  $\pi_l \in [0, 1]$  is the attribute-level of the  $l^{\text{th}}$  attribute. Further, recall a buyer's multi-attribute valuation function from Equation 4.7 is defined as:

$$v_{b_i}(\pi) = \lambda_{b_i} \left[ \sum_{l=1}^n w_l^{b_i} u_{b_i}(\pi_l) \right] \times \prod_{l=1}^n \delta(\pi_l).$$

#### 4.5. AN ALGORITHM FOR MEASURING ALLOCATIVE EFFICIENCY

Let us assume, in a simple case, that the buyer has no minimum or maximum constraints:  $\forall_l, r_{l_i}^{b_i} = 0.0, r_{l_i}^{b_i} = 1.0$ ; the  $u_{b_i}$  and  $\delta(\pi_l)$  terms become unity, and the valuation function reduces to:

$$v_{b_i}(\pi) = \lambda_{b_i} \sum_{l=1}^n w_l^{b_i} \pi_l \quad (4.35)$$

Assuming the same logic for a seller's cost function  $c_{s_j}(\pi)$  (Equation 4.10), the overall utility of a transaction between the buyer and seller becomes:

$$\begin{aligned} u_{b_i, s_j} &= \lambda_{b_i} \left[ \sum_{l=1}^n w_l^{b_i} \pi_l \right] - \lambda_{s_j} \left[ \sum_{l=1}^n w_l^{s_j} \pi_l \right] \\ &= \sum_{l=1}^n \lambda_{b_i} \cdot w_l^{b_i} \cdot \pi_l - \lambda_{s_j} \cdot w_l^{s_j} \cdot \pi_l \end{aligned} \quad (4.36)$$

Based on this analysis, and knowing that  $\forall_l, \lambda_{b_i} w_l^{b_i} \geq 0$  and  $\lambda_{s_j} w_l^{s_j} \geq 0$ , solving the optimisation problem in Equation 4.34 is merely a matter of either maximising or minimising each attribute-level  $\pi_l \in \pi$ , depending on the limit prices and preferences in Equation 4.36. Importantly though, trader attribute constraints should be respected:

$$\forall_{\pi_l \in \pi}, \pi_l \in [r_{l_i}^{b_i}, \min(r_{l_i}^{b_i}, r_{l_i}^{s_j})]$$

That is, the attribute-level cannot be below the buyer's minimum constraints or above the seller's maximum constraints, and there is no value in exceeding the buyer's maximum constraints. Given these constraints, it is possible to find  $\pi^*$  by finding the optimal level  $\pi_l^*$  of each attribute:

$$\forall_{\pi_l^* \in \pi^*}, \pi_l^* = \begin{cases} \min(r_{l_i}^{b_i}, r_{l_i}^{s_j}) & \text{if } (\lambda_{b_i} w_l^{b_i}) - (\lambda_{s_j} w_l^{s_j}) \geq 0 \\ r_{l_i}^{b_i} & \text{otherwise.} \end{cases} \quad (4.37)$$

Intuitively, if the buyer gets more value out of a given increase in an attribute-level than it costs the seller to produce said increase, maximise the attribute within constraints. If the cost to the seller is larger than the increase in

buyer value, then minimise the attribute level. Finally, the OMRA algorithm, for finding the total utility  $U(\Theta^*)$  of the optimal allocation  $\Theta^*$ , within our multi-attribute market-based system is presented in Algorithm 4.3.

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**Algorithm 4.3** Optimal Multi-attribute Resource Allocation (OMRA) Algorithm

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```

1: Create a utility matrix  $U$  of size  $\mathcal{B}$ -by- $\mathcal{S}$ .
2:
3: for all  $b_i \in \mathcal{B}$  do
4:   for all  $s_j \in \mathcal{S}$  do
5:     for all  $\pi_l \in \pi$  do {find optimal resource  $\pi \equiv \pi^*$  for  $b_i$  and  $s_j$ }
6:        $\pi_l \leftarrow \pi^*$  {set the attribute to the optimal level}
7:     end for
8:      $u_{b_i, s_j}^* \leftarrow \max(v_{b_i}(\pi^*) - c_{s_j}(\pi^*), 0)$  {ensure  $u_{b_i, s_j}^*$  non-negative}
9:   end for
10: end for
11:
12: Run Hungarian Algorithm on utility matrix  $U$ .

```

---

## 4.6 Conclusions and Discussion

This chapter has introduced a novel model for allocating multi-attribute computational resources via competing marketplaces. Traders choose to trade in the markets for resources that most satisfy their preferences and constraints, while marketplaces choose what type of resource should be traded within their markets. This model of resource allocation is novel because it is the first to explicitly consider the allocation of multi-attribute resources via multiple double auction marketplaces. Developing such a model required developing several new behaviour models and algorithms not considered within the literature; specifically:

- Previous approaches to modelling how traders value multi-attribute resources [11, 163] often consider only additive value functions [47], where the utility of an attribute cannot affect any other. This is not representative of the type of preferences and constraints computational consumers might have, thus new decision-making behaviours were developed in this chapter inspired by marketing models grounded in consumer theory.

#### 4.6. CONCLUSIONS AND DISCUSSION

- As well as being able to value multi-attribute computational resources, traders are also able to integrate charges and fees into their bidding strategies.
- Given the multi-attribute resource trader valuation models, there are no previous approaches for explicitly calculating the optimal allocation of resources between traders. This chapter provided such an algorithm.

Within this chapter, by considering two-attribute computational resources, visualisations of buyer valuation, seller cost, and total transaction surplus, for different types of resource, demonstrated that outcomes of interactions between traders can be significantly affected by the resource traded. This highlights the most immediate challenge that needs to be tackled in order for this approach to be feasible, and demonstrable:

- In order for efficient allocations to be achieved using this approach, traders must be able to trade the resources that most match their preferences and constraints, thus market-exchanges require strategies that allow them to *autonomously* locate the *market niches* in the attribute-level space that most satisfy traders. This challenge is tackled in Chapter 5.

Overall, the contributions of this chapter are:

- A model of resource allocation for multi-attribute computational resources via competing double-auction marketplaces;
- Decision-making models for buyers and sellers based on multi-attribute utility functions and grounded in modern consumer theory;
- Visualisations highlighting the impact that trader preferences and constraints have on the transaction outcomes of different resource types;
- An extension to previous market-selection strategies [118, 24] using consideration sets, which allow traders to avoid inept resources, and select the most appropriate market to join;
- An algorithm for calculating the total utility of a system of traders with potentially different preferences and constraints, which can be used in future chapters to measure the allocative efficiency of the approach.

Finally, it is not within the scope of this thesis to directly compare this model with other approaches to multi-attribute resource allocation. This is because the usefulness of resource allocation approaches depends on the the objectives the system designer is trying to meet, e.g., efficiency, robustness, scalability. Thus, it is hard to compare this approach to, say, a single centralised multi-attribute auction approach [13] or a fully decentralised CATALAXY approach [3]; however, future work will consider multi-objective methods for at least identifying approaches that may empirically *dominate* others on all considered objectives.

**CHAPTER 5**

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**MECHANISMS FOR MARKET  
NICHING**

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In Chapter 4, a model of multi-attribute resource allocation via competing marketplaces was proposed and formally developed. The approach proposed is, rather than allocating complex computational multi-attribute resources via a single centralised mechanism (computationally complex, and potentially brittle) or using fully decentralised approaches (often requiring complex negotiating strategies), resources could be allocated via distributed markets, using double-auction mechanisms run by market-exchange agents. This chapter considers, for the first time, the *automatic market niching problem*, where market-exchanges must *autonomously* select the types of resources that should be traded within their market in the presence of other competing and *coadapting* competitors attempting to do the same. Using two reinforcement learning approaches, several algorithms, called *attribute-level selection* (ALS) strategies, are considered for dealing with the problem. Encouraged by the results from the application of the methodology presented in Chapter 3, which suggested market mechanisms can be brittle, or obversely robust, to different environmental factors, by applying the same methodology, the performance of the attribute-level selection strategies are empirically assessed in a variety of *representative* marketplace environmental contexts in a bid to learn more about their general ability.

The main contributions of this chapter are: (i) to provide the first clear description of the automatic market niching problem, and propose several candidate attribute-level selection strategies for tackling it, based on n-armed bandit and evolutionary optimisation approaches; (ii) to identify, via a comprehensive computational study involving some 18,300 separate simulations, which environmental factors influence the performance of different attribute-level selection strategies on the automatic market niching problem; and (iii) to demonstrate that in bilateral simulations, competing market-exchanges can self-organise and cover all market-niches within an environment, leading to desirable resource allocations. Although this chapter does not fully answer the

## 5.1. MOTIVATION

question of which is the best attribute-level selection strategy *in general*, it makes a significant step forwards towards understanding how the performance of different attribute-level selection strategies are affected by various environmental factors, which enables the suitability of reinforcement learning approaches to be clearly studied, in this newly formulated problem.

The outline of the rest of this chapter is as follows. In Section 5.1, the specific work undertaken within this chapter is more clearly motivated, the *automatic market niching problem* is formulated, and specific research questions are posed. In Section 5.2 two approaches for tackling the automatic market niching problem are proposed, and six candidate *attribute-level selection strategies* are defined. Applying the methodology developed in Chapter 3, representative *environmental contexts* are defined in Section 5.3, by considering representative trader preferences and constraints as well as market-exchange charging schemes. In Section 5.4 the ability of attribute-level selection strategies to find market niches is empirically assessed, while work in Section 5.5 focusses on emergent properties of the niching process between competing marketplaces in multi-niche environments. Finally, the chapter is concluded and a brief discussion is provided in Section 5.6.

## 5.1 Motivation

The model in Chapter 4 proposes that market-exchanges can specify which type of resource should be traded within their market, and resources can be allocated in each market using a computationally efficient continuous double auction mechanism. A significant question left unanswered from Chapter 4 is how market-exchange agents should best select which types of resources should be traded within their markets. The strategy used to make those decisions—an *attribute-level selection strategy*—will significantly affect the utility, i.e., profits, of the market-exchange agents, which are a function of volume of traders joining



and trading within their markets.

Real-world decisions over which multi-attribute resources to provide a market for, e.g., in Options and Futures market, or virtual machines instances in Amazon's *Web Services* portal [2], are made by experienced human experts, who are usually fully aware of, or able to accurately estimate, supply and demand schedules. However, market-exchange agents must make these decisions *autonomously*, without human intervention. Thus, a detailed understanding of the different potential attribute-level selection strategies is important, particularly if one seeks to eventually automate the design of complete market mechanisms for this type of resource allocation.

### 5.1.1 Automatic market niching

In essence, the *automatic market niching problem* can be summarised as follows. At the beginning of each trading day, a market-exchange must define the type of multi-attribute resource that can be traded within its single market. Recall, a resource  $\pi$  is described over a vector of  $n$  individual attributes:

$$\pi = \langle \pi_1, \pi_2, \dots, \pi_n \rangle$$

where  $\pi_j \in \mathbb{R}_{\geq 0}$  is the level of the  $j^{\text{th}}$  attribute. Market-exchanges define the resource to be traded in their market by setting each of the attribute-levels using an attribute-level selection strategy; their decision is then made available to all traders in the environment.

Traders, being expected utility maximisers, prefer markets where the resources being traded, i.e., the attribute-levels of the chosen resource, best align with their preferences and constraints. A reasonable assumption is that while traders' preferences and constraints can be unique, cohorts of traders exist within *market segments* [89, p. 73]. Different market segments prefer to trade different resources, and a natural consequence of competitive traders is that they will

## 5.1. MOTIVATION

migrate to markets that satisfy their segment. Market-exchanges, also being expected utility maximisers, therefore need to identify resource types i.e., vectors of attribute-levels, that satisfy market segments. The process of discovering these segments is called *market niching*, and the product or service that satisfies a market segment is called a *market niche*. Thus, the automatic market niching problem is one of finding market niches via searching the *attribute-level space* for vectors of attributes that form resource which satisfy a market segment.

The main research challenge is to take this problem of finding market-niches, frame it in a way that allows market-exchange agents to tackle it, and develop suitable attribute-level selection strategies. However, this is challenging for a number of reasons:

1. In realistic scenarios, trader preferences and constraints, and thus market niches, are unknown *a priori*; they must be learnt over time, but they are also a *moving target*, because they can change;
2. At any time, one can associate each point in the attribute-level space with an expected reward, yet the mapping between a point in the attribute-level space and a daily profit, i.e., the *fitness function*, changes over time:
  - (a) because the traders' preferences and constraints may change over time;
  - (b) because competing market-exchanges may advertise different or identical attribute-levels, which may change the number and type of trader an exchange could attract with its current attribute-levels;
3. There is an *exploration* versus *exploitation* problem between trying new points in attribute-level space and selecting the best found so far [99, 72, 164];
4. Depending on how the environment—the trader population, other competing market-exchanges, and how the traders are charged—changes, some mechanisms that do well in one environment may not generalise well to other unknown environments.

It is very unlikely that a single algorithm, in the form of an attribute-level selection strategy, would be best over all environments, because the environment is complex, adaptive, and coevolving. Thus, in reality there are two learning processes going on: a population of exchanges competing and learning which

types of resources to offer in their markets, and a population of traders competing over resource by learning which markets to join. However, progress can be made on this problem by identifying what impacts different environmental factors have on market niching algorithms, and specifically what approaches work well and why.

### 5.1.2 Research questions

On such a novel problem, with a solution needing to satisfy many clear challenges, it is not possible to initially tackle the ultimate problem of what is the best algorithm to solve the market niching problem. After all, it encompasses many aspects of decision theory [138], agent-based computational economics [167, 91], and online machine learning [178], all with many open questions. This chapter makes an initial start on this novel problem by working towards answering the following research questions:

- *How are candidate attribute-level selection strategies' performance properties affected across different environmental situations, and can any be seen to generalise across all the environments?*
- *What impact do different environmental situations have on competing attribute-level strategies' abilities to find market niches in multi-niche environments?*

## 5.2 Attribute-level Selection Strategies

Attribute-level selection strategies provide market-exchange agents with a mechanism for automatically selecting the levels of the attributes of the resources that are traded in their markets. Different levels of resources, i.e., different points in the *attribute-level space*, will affect how attractive an exchange's market is to traders, and thus the exchange's ability to generate revenue from charges and fees.

## 5.2. ATTRIBUTE-LEVEL SELECTION STRATEGIES

Assuming a population of traders with potentially different preferences and constraints over resource attributes, it is likely that certain points in the attribute-space will correlate with *market niches*. That is, different *segments* of the trading population would prefer to trade different types of resources. Satisfying these market niches by providing markets for trading the most desired resources will increase the allocative efficiency of the system, indicating overall higher profits for traders, which in turn means more revenue for market-exchanges. Similarly to traders having to make decisions over joining multiple market-exchanges, market-exchanges face a tradeoff between exploration and exploitation. They must balance exploring the attribute-level space, by regularly changing the type of resource they offer in their market, with exploiting the best resource type found so far.

Given the environment is dynamic and coevolving—because of other market-exchanges’ decisions, and trading agents’ learning—the typical revenue generated from traders *changes over time*, and market-exchanges must constantly explore the attribute-level space to identify the most lucrative types of resource to be traded in their markets. With that in mind, it is proposed that in general, attribute-level selection strategies follow Algorithm 5.1. In essence,

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**Algorithm 5.1** The general attribute-level selection strategy algorithm

---

```

1: Choose appropriate evaluation period length  $\ell$ .
2: for all trading days  $t$  do
3:   if  $t \bmod \ell == 0$  then {end of evaluation period  $\eta$ }
4:      $Q_{\pi_i} \leftarrow \widehat{r}_{\pi_i}^\eta / \ell$  {record mean evaluation period reward.}
5:      $\pi_i \leftarrow \pi_j$  {select new resource type  $\pi_j$  (according to strategy).}
6:      $\eta \leftarrow \eta + 1$  {next evaluation period.}
7:   else
8:      $\widehat{r}^\eta \leftarrow \widehat{r}^\eta + r^t$  {update evaluation period reward with daily reward.}
9:   end if
10: end for

```

---

attribute-level selection strategies evaluate a resource type for a number of days, called an evaluation period. Once the evaluation period is finished, the reward in terms of the mean daily market profit over the period, is recorded, and a new

resource type chosen through the selection of new attribute-levels. Thus, the evaluation period is used to dampen any oscillations in daily market profits due to the dynamic nature of the environment. In all simulations within this chapter  $\ell = 10$ , though values between 5–15 seemed to work equally well.

### 5.2.1 Attribute-level selection as a bandit problem

The problem of choosing optimal attribute-levels for two attribute resources can be framed as a *multi-armed bandit problem* (MAB) [9]. A MAB models a world where an agent chooses from a finite set of possible *actions* (levers on a bandit slot machine), and executing each action results in a *reward* for the agent (winnings from pulling the lever). In the MAB problem formulation, rewards for actions are distributed according to real probability distributions [164], and each action has a distribution associated with it.

In the simplest MAB problem, the distributions associated with each lever do not change over time [142], while some versions of the problem allow the distribution associated with an action to change when that action is chosen, or even allow new actions to become available over time [177]; in such a case, the *environmental state* the agent finds itself in, changes. However, what sets the *attribute-level selection problem* apart from these situations is that not *only* can the reward distributions of chosen actions change every time an action is executed, but the reward distributions of *unchosen actions* can, too. This means, for example, that an action with seemingly poor rewards over some time horizon may in fact turn out to have excellent rewards during some future time horizon. In the literature, bandit problems such as these are often referred to as *Restless Bandit Problems* [178].

Framing the attribute-level selection problem in this way assumes each of the resource attributes have  $n$  discrete levels, which is not a strong assumption given current real-world utility computing providers, such as Amazon Web Services [2], only provide a relatively small selection of the most popular

## 5.2. ATTRIBUTE-LEVEL SELECTION STRATEGIES

computational resource types. For this model, it is assumed each resource attribute  $\pi_j$  can take  $n = 5$  distinct levels:

$$\forall_{\pi_j \in \pi} \pi_j \in \{0.2, 0.4, 0.6, 0.8, 1.0\} \quad (5.1)$$

A non-zero minimum level is chosen because in reality, most if not all computational resources need at least some level of each attribute to be desirable. Given  $q$  attributes, there are  $n^q = 25$  possible two-attribute resource types. Each market-exchange  $m_k$ 's attribute-level selection strategy maintains an *action set*  $\Pi$  of all possible actions,

$$\Pi = \{\pi_1, \pi_2, \dots, \pi_{q^n}\} \quad (5.2)$$

Thus, each action represents a type of resource, which is a vector of attribute-levels, and therefore a single point in the attribute-level space. Each market-exchange  $m_k$ 's ALS strategy maintains a *reward set*  $\mathbf{Q}^{m_k}$ :

$$\mathbf{Q}^{m_k} = \langle Q_{\pi_1}^{m_k}, Q_{\pi_2}^{m_k}, \dots, Q_{\pi_{q^n}}^{m_k} \rangle \quad (5.3)$$

where  $Q_{\pi_i}^{m_k}$  would be the historical reward associated with action  $\pi_i$ . Next, some MAB-based attribute-level selection strategies are discussed to help choose between actions.

### $\epsilon$ -greedy strategy

$\epsilon$ -greedy is one of the most widely studied and earliest used bandit strategies [164, p. 28]. It is called a *semi-uniform strategy* because it explores all actions with equal probability.  $\epsilon$ -greedy is one of the simplest bandit strategies, and uses a single parameter,  $\epsilon \in [0, 1.0]$ , to represent the probability of choosing a random action, i.e., exploring. The strategy behaves in an exploitative way, and chooses the action with the best historical reward, with probability  $1 - \epsilon$ .

**$\varepsilon$ -decreasing strategy**

While  $\varepsilon$ -greedy has a static  $\varepsilon$ , i.e., one that does not change while the strategy is in use, the  $\varepsilon$ -decreasing [164] strategy adjusts its value for  $\varepsilon$  over time according to a predetermined schedule, based on a parameter  $\delta \in [0, +\infty)$ . For a time  $t$ ,  $\varepsilon$  is determined by:

$$\varepsilon_t = \min\left(\frac{\delta}{t}, 1\right) \quad (5.4)$$

$\varepsilon$ -decreasing is also a *semi-uniform* strategy. Typically,  $\delta$  is set such that the resulting  $\varepsilon_t$  from Equation 5.4 is initially large, resulting in very explorative behaviour, but eventually very exploitative behaviour.

**Softmax strategy**

Semi-uniform strategies, when exploring, choose actions with historically bad rewards as often as any other. This can be detrimental when the worst actions are *very* bad. The *Softmax* [164, p. 30] bandit strategy attempts to avoid these very bad actions by choosing all actions with probability *proportional* to their historical rewards. Typically, Gibbs or Boltzmann distributions [62, p. 3] are used for probability distributions. An action  $\pi_i$  is selected with probability  $\psi_{\pi_i}$ , where:

$$\psi_{\pi_i} = \frac{e^{Q_{\pi_i}^{m_k}/\tau}}{\sum_{j=1}^{|\mathbf{Q}|} e^{Q_{\pi_j}^{m_k}/\tau}}, \quad (5.5)$$

where  $Q_{\pi_i}^{m_k}$  refers to the  $m_k$ 's historical reward for action  $\pi_i$ . Probabilities are normalised across the entire reward set  $\mathbf{Q}$ . The temperature  $\tau$  shapes the distribution; when a relatively high temperature is chosen, all actions are chosen with approximately equal probability, while a low temperature causes a greater gap in the probabilities of choosing different actions. At the limit  $\tau \rightarrow 0$ , *Softmax* becomes a purely greedy strategy [164, p. 30].

## 5.2. ATTRIBUTE-LEVEL SELECTION STRATEGIES

### Rank-based strategy

The *Rank-based strategy* is a novel strategy inspired by the *rank selection* genetic operator often used to maintain diversity in genetic algorithms [107, pp. 169–170]. Like *Softmax*, the probability of choosing an action is proportional to its historical rewards, however, the probability of choosing it is independent of the *quantitative* value of the historical reward, only its performance rank, relative to the others. Thus, in the case of action  $\pi_i$ , the probability  $\psi_i$  of it being chosen is:

$$\psi_i = \frac{\text{rank}(\pi_i)^\zeta}{\sum_{j=1}^n \text{rank}(\pi_j)^\zeta}, \quad (5.6)$$

where  $\zeta$ , the selection pressure, again controls the tradeoff between exploration and exploitation. The function  $\text{rank}(\pi_i)$  outputs the rank of action  $\pi_i$  based upon its historical reward  $Q_{\pi_i}^{m_k}$ ; the action with the best historical reward is ranked  $|\mathbf{Q}|$ , while the action with the lowest ranked 1.

### Rewards in non-static environments

The attribute-level selection problem is a *non-stationary* problem, because many agents, through interactions over time, are learning and adapting their behaviour. Therefore, it is important that the rewards  $Q \in \mathbf{Q}$  associated with the resource types  $\pi \in \mathbf{\Pi}$ , i.e., the actions, are updated appropriately. Using the same approach traders take when updating their market-selection signals, a market-exchange  $m_k$  can update the reward  $Q_{\pi_i}^{m_k}$  for action  $\pi_i$  in the next time-step  $t + 1$ , can be done as follows:

$$Q_{\pi_i}^{m_k}(t + 1) = Q_{\pi_i}^{m_k}(t) \cdot \delta [r_{\pi_i}^t - Q_{\pi_i}^{m_k}(t)] \quad (5.7)$$

where  $r_{\pi_i}^t$  is *instantaneous reward* that the action returned in time-step  $t$ ; in this model, that equates to the profit the market-exchange made on trading day  $t$ .



### 5.2.2 Attribute-level selection as an optimisation problem

Reducing the number of possible resources an ALS strategy can choose from, through discretising the attribute-level space, can be useful for effective exploration. However, a possible disadvantage to this discretisation process is that if there is a relationship between points in the attribute-level space, and the rewards that those points provide, bandit strategies cannot leverage this, because they do not consider the relationship between actions in the attribute-level space.

Evolutionary optimisation algorithms [187] work on the principle that improving solutions are often found close by, so algorithms tend to search in and around neighbouring points in the space; this is often appropriate if the fitness function being optimised is continuous. However, the more discrete the fitness landscape is, the more chance there is of encountering *local optima*, in which case meta-heuristic algorithms can get stuck [42].

Recall the two-attribute resource visualisations in Section 4.2.3 on Page 91. Within these visualisation there is certainly a relationship between some neighbouring points in the attribute-level space and the total utility of the transactions over the resource described by those attributes-levels. Thus, the attribute-level selection problem can be framed as an optimisation problem by re-defining the set  $\Pi$  of possible resource types to be vectors of real-value attribute-levels.

$$\Pi = \{\pi : \forall \pi_j \in \pi, \pi_j \in \mathbb{R}_{\geq 0}\} \quad (5.8)$$

Therefore, resource types can be treated as potential solutions, proposed by a evolutionary optimisation algorithm. In terms of the general attribute-level selection strategy algorithm (Algorithm 5.1), the evaluation period  $\eta$ 's reward  $\widehat{r}_{\pi_i}^\eta$ , for selecting resource  $\pi_i$ , becomes the *fitness* assigned to the solution  $\pi_i$ .

## 5.2. ATTRIBUTE-LEVEL SELECTION STRATEGIES

### 1+1 ES

The *1+1 ES*, or *1+1 Evolutionary Strategy* [10], is a very simple evolutionary algorithm, which harnesses the ideas of adaptation and evolution. It has a population size of two, consisting of the current best individual (the parent), and a candidate next solution (the offspring). Each individual represents a resource type  $\pi$  in the form of a vector of two attribute-levels where, maintaining the same range as for the bandit approach,  $\forall \pi_j \in \pi, \pi_j \in [0.2, 1.0]$ . When this attribute-level selection strategy is used, a new offspring individual  $\pi_o$  is generated each evaluation period using a mutated copy of the the parent  $\pi_p$ . Mutation is carried out through perturbing each attribute-level  $\pi_j \in \pi_p$  by a value drawn from the Gaussian distribution  $N(\pi_j, \sigma)$ , where  $\sigma$  is the standard deviation. The offspring is used as the resource type for the exchange's market during the next evaluation period, and if its fitness is larger than the parent's, it becomes the new parent:

$$\pi_p \leftarrow \pi_o \iff \widehat{r}_{\pi_o}^\eta > \widehat{r}_{\pi_p}^{\eta-1} \quad (5.9)$$

where  $\widehat{r}_{\pi_o}^\eta$  is the reward, or *fitness*, that the offspring resource  $\pi_o$  got in evaluation period  $\eta$ , and  $\widehat{r}_{\pi_p}^{\eta-1}$  is the fitness of the parent resource  $\pi_p$  as of the previous evaluation period  $\eta - 1$ .

### Evolutionary Algorithm (EA)

An *EA*, or *Evolutionary Algorithm* is a broad term for a family of population-based evolutionary optimisation algorithms. Unlike the the *1+1 ES*, it is assumed the *EA* algorithm maintains a population size of greater than two individuals at all times. The most popular type of population based evolutionary algorithm, the *genetic algorithm*, can use a variety of different genetic operators to control how the algorithm evaluates, selects, and reproduces individuals.

Within this chapter, *tournament selection* [105] is used to decide which members of the population are combined to form new offspring solutions. The

selection technique is steady-state because the algorithm can search the solution space without having to evaluate the entire population before proceeding. For this strategy,  $k = 3$  individuals are randomly selected from the population, and evaluated over three consecutive evaluation periods  $\eta, \eta + 1, \eta + 2$ , by deploying them as the resource type for the exchange's market. From the  $k$  individuals, the two with the highest evaluation period rewards, i.e., fitness, are recombined using *mutation* and *cross-over* genetic operators [42, p. 300] to create two new offspring solutions. The weakest of the  $k$  individuals is replaced by one of the offspring individuals (selected with uniform probability).

### 5.3 Defining Environmental Contexts

The results of Chapter 3 showed that in general, the performance of market mechanisms can be sensitive to a number of environmental factors, and thus market mechanisms can be seen to be robust (or obversely, brittle) to different environments. Chapter 3's results were attained by using a methodology for empirically assessing the generalisation properties of the market mechanisms, via simulations using a curated set of environmental contexts. The principal approach of the methodology is to identify the main building blocks of the environment—the notions that *define* the environment—and generate a set of *representative environments*, from these.

Within this chapter, the same methodology is applied so that the performance and impact of various attribute-level selection strategies can be empirically analysed. The model of resource allocation considered within this thesis assumes an environment defined in three ways: (i) by the general makeup of the trading population, particularly in terms of their preferences and constraints over resources; (ii) by the charging schemes used by the market-exchanges, which affects the behaviour of traders within the trading population; and (iii) both the presence of, and the strategies in use by, competing

### 5.3. DEFINING ENVIRONMENTAL CONTEXTS

market-exchanges. Each of these individual *contexts* affect and change the overall *environmental context*.

#### 5.3.1 Representative trader contexts

Within this section several *trader contexts* are proposed, which are defined by a population of traders, each with potentially different preferences and constraints over the attributes of multi-attribute resources. There are clearly *many* possible ways of configuring the parameters of a population of trading agents, so it is sensible to consider a reduced but representative set for simulations. The methodology from Chapter 3 proposed a sensible way of reducing the number of possible contexts by only considering boundary or extreme variations; for example, trader mixes were typically defined by the presence or absence of only one type of trading strategy, rather than *medial* mixes of different strategies.

Because this is an initial study into the performance and impact of attribute-level selection strategies, attention is restricted to trader contexts that have well-defined niches, due to them being easier to find. As discussed in Section 5.1.1, a market niche is well-defined when there exists a significant proportion of traders that all share similar preferences and constraints, and thus prefer to trade within the same market. Further, in order to better understand the impact that constraints and preferences have on the performance of attribute-level selection strategies, they are separated into different contexts. The proposed representative niches are now described.

##### ‘Unconstrained single niche’ trader context

The *unconstrained single niche* trader context is defined by the simplest possible population of traders, held in the set  $\mathcal{T}^{\text{US}}$ . Each trader  $a_i \in \mathcal{T}^{\text{US}}$  has the following

preferences and constraints:

$$\begin{aligned}
 \forall a_i \in \mathcal{T}^{\text{US}}, \\
 \mathbf{w}^{a_i} &= \langle 0.5, 0.5 \rangle \\
 \mathbf{r}_{\downarrow}^{a_i} &= \langle 1.0, 1.0 \rangle \\
 \forall a_i \in \mathcal{B} \cap \mathcal{T}^{\text{US}}, \\
 \mathbf{r}_{\downarrow}^{a_i} &= \langle 0.2, 0.2 \rangle \\
 \forall a_i \in \mathcal{S} \cap \mathcal{T}^{\text{US}}, \\
 \mathbf{r}_{\downarrow}^{a_i} &= \langle 0.0, 0.0 \rangle
 \end{aligned} \tag{5.10}$$

Thus, neither buyers or sellers have any maximum constraints over attributes, and buyers only have minimal minimum constraints. Figure 5.1 shows a visualisation of the maximum theoretical utility (in terms of total daily profit) for a random instance of this trader context, calculated by using the *optimal multi-attribute resource allocation* algorithm, first presented in Chapter 4. Because there is only a single well-defined market niche, in a two market-exchange environment both exchanges would most likely have to compete over it for traders. Cai et al. [23], for example, have observed in other domains, that competitive traders will migrate in groups to the most profitable markets. In this system, given two identical markets sharing a single niche, it is likely the traders will all eventually migrate to a single market, because the increased *liquidity* from all being in one market increases expected profits. Thus, it is likely that attribute-level selection strategies that can quickly locate the niche may end up performing better in bilateral simulations.

#### ‘Constrained single niche’ trader context

The *constrained single niche* trader context is defined by a population of traders, held in the set  $\mathcal{T}^{\text{CS}}$ . Each trader  $a_i \in \mathcal{T}^{\text{CS}}$  has the following preferences and

### 5.3. DEFINING ENVIRONMENTAL CONTEXTS

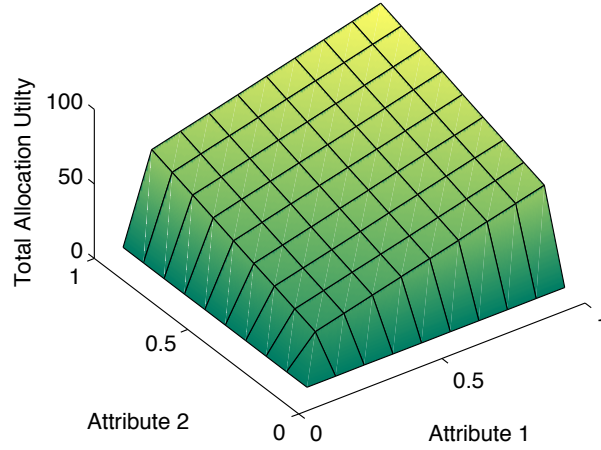


Figure 5.1: Maximum theoretical daily total trader profit for a randomly generated *unconstrained single niche* trader context. Given the lack of preferences and maximum constraints, each trader  $a_i \in \mathcal{T}^{\text{US}}$  would prefer to trade in a market where  $\pi = \langle 1.0, 1.0 \rangle$  is the type of resource being traded. Thus, there is a single well-defined market niche within the attribute-space, at point  $\langle 1.0, 1.0 \rangle$ .

constraints:

$$\begin{aligned}
 \forall a_i \in \mathcal{T}^{\text{CS}}, \\
 \mathbf{w}^{a_i} &= \langle 0.5, 0.5 \rangle \\
 \forall a_i \in \mathcal{B} \cap \mathcal{T}^{\text{CS}}, \\
 \mathbf{r}_\downarrow^{a_i} &= \langle 0.2, 0.2 \rangle \\
 \mathbf{r}_\uparrow^{a_i} &= \langle 0.6, 0.6 \rangle \\
 \forall a_i \in \mathcal{S} \cap \mathcal{T}^{\text{CS}}, \\
 \mathbf{r}_\downarrow^{a_i} &= \langle 0.0, 0.0 \rangle \\
 \mathbf{r}_\uparrow^{a_i} &= \langle 1.0, 1.0 \rangle
 \end{aligned} \tag{5.11}$$

As shown in Figure 5.2, the trader context also has a single market niche, but the buyers within the population have maximum constraints resource attributes. Thus, while buyers can trade with sellers for resources comprising attribute above their maximum constraints, the total utility decreases more as constraints are

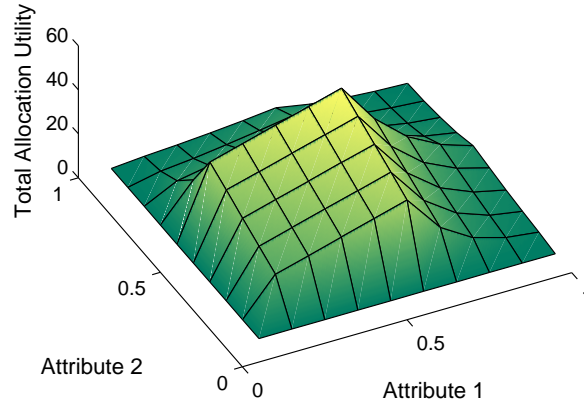


Figure 5.2: Maximum theoretical daily total trader profit for a randomly generated *constrained single niche* trader context. Each buyer  $a_i \in \mathcal{B} \cap \mathcal{T}^{\text{CS}}$  would prefer to trade in a market where  $\pi = \langle \geq 0.6, \geq 0.6 \rangle$  is the type of resource being traded. Because sellers' production costs increase with attribute-levels, the total utility from a transaction typically decreases as the attribute-levels increase. Thus, total trader utility (in terms of profit) is maximised at the single point when resources being traded are of the type  $\pi = \langle 0.6, 0.6 \rangle$ , indicated the presence of a well-defined niche at that point.

exceeded, because the buyers receive no extra value and the sellers' costs increase. Therefore, a single well-defined market niche exists at a point where buyers are happiest and sellers' costs are minimised, which in this example is at the point  $\pi = \langle 0.6, 0.6 \rangle$ . In contrast to the unconstrained single niche context, where traders' abilities to trade with each other are only affected by their budgets, traders within this context may find that, depending on the type of resource being traded, their constraints make it harder to successfully trade in the market.

#### 'Constraint-induced niches' trader context

The *constraint-induced niches* trader context is defined by a trading population  $\mathcal{T}^{\text{CI}}$  that contains *two* sub-populations of traders,  $\mathcal{T}_1^{\text{CI}}$  and  $\mathcal{T}_2^{\text{CI}}$ . Each trader  $a_i$  is a member of exactly one of the sub-populations, thus:

$$\mathcal{T}^{\text{CI}} = \{a_i : (a_i \in \mathcal{T}_1^{\text{CI}}) \oplus (a_i \in \mathcal{T}_2^{\text{CI}})\} \quad (5.12)$$

### 5.3. DEFINING ENVIRONMENTAL CONTEXTS

The two sub-populations are defined as follows. The first sub-population,  $\mathcal{T}_1^{\text{CI}}$ , contains buyers with preferences and constraints equivalent to those in the *constrained single niche* trader context, previously defined in Equation 5.11:

$$a_i \in \mathcal{B} \cap \mathcal{T}_1^{\text{CI}} \iff a_i \in \mathcal{B} \cap \mathcal{T}^{\text{CS}} \quad (5.13)$$

while the sellers have the following:

$$\begin{aligned} \forall a_i \in \mathcal{S} \cap \mathcal{T}_1^{\text{CI}}, \\ \mathbf{w}^{a_i} &= \langle 0.5, 0.5 \rangle \\ \mathbf{r}_{\downarrow}^{a_i} &= \langle 0.0, 0.0 \rangle \\ \mathbf{r}_{\uparrow}^{a_i} &= \langle 1.0, 1.0 \rangle \end{aligned} \quad (5.14)$$

The second sub-population,  $\mathcal{T}_2^{\text{CI}}$ , contains traders with the following preferences and constraints:

$$\begin{aligned} \forall a_i \in \mathcal{T}_2^{\text{CI}}, \\ \mathbf{w}^{a_i} &= \langle 0.5, 0.5 \rangle \\ \forall a_i \in \mathcal{B} \cap \mathcal{T}_2^{\text{CI}}, \\ \mathbf{r}_{\downarrow}^{a_i} &= \langle 0.8, 0.8 \rangle \\ \mathbf{r}_{\uparrow}^{a_i} &= \langle 1.0, 1.0 \rangle \\ \forall a_i \in \mathcal{S} \cap \mathcal{T}_2^{\text{CI}}, \\ \mathbf{r}_{\downarrow}^{a_i} &= \langle 0.0, 0.0 \rangle \\ \mathbf{r}_{\uparrow}^{a_i} &= \langle 1.0, 1.0 \rangle \end{aligned}$$

Within this trader context, the ideal interactions between agents within the two trader sub-populations, leads to two well-defined market niches. The reader should note that the relative height of the peaks does not impact on the number



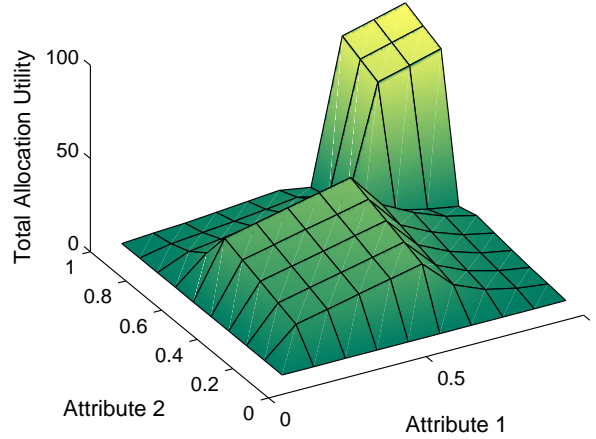


Figure 5.3: Maximum theoretical daily total trader profit for a randomly generated *constraint-induced niches* trader context. Some buyers,  $a_i \in \mathcal{B} \cap \mathcal{T}_1^{\text{CI}}$ , would prefer to trade in a market where  $\pi = \langle \geq 0.6, \geq 0.6 \rangle$  is the type of resource being traded. Other buyers,  $a_i \in \mathcal{B} \cap \mathcal{T}_2^{\text{CI}}$ , would prefer  $\pi = \langle 1.0, 1.0 \rangle$ , and would be unwilling to accept any resource where  $\pi = \langle < 0.8, < 0.8 \rangle$ . Further, some sellers,  $a_i \in \mathcal{S} \cap \mathcal{T}_1^{\text{CI}}$ , can only produce resources where  $\pi = \langle \leq 0.6, \leq 0.6 \rangle$ . This results in a situation where total trader profits are maximised when the two populations traded within separate markets: one market for the resource type  $\pi = \langle 0.6, 0.6 \rangle$ , and the other market for the resource type  $\pi = \langle 1.0, 1.0 \rangle$ . Therefore, there are *two* well-defined market niches that market-exchanges could satisfy.

of niches in the environments. For example, suppose that the taller of the two niches in Figure 5.3 was more than twice the height of the lower niche. Initially one might expect two market-exchanges to share the taller niche, because half of the total utility available there is more than that at the lower niche. However, because traders are able to migrate easily between markets, and a larger single market is typically more efficient than two separate markets, all the traders will inevitably migrate to the same exchange. In such a case, the exchange that loses the traders will be forced to move down to the second lower niche. Thus, to satisfy the traders within this trader context requires multiple market-exchanges, which must provide separate markets for each market niche. While some traders could feasibly trade resources described by any point in the attribute-space, some points in the space will be infeasible to many traders.

### 5.3. DEFINING ENVIRONMENTAL CONTEXTS

#### ‘Preference-induced niches’ trader context

The *preference-induced niches* trader context is defined by a trading population  $\mathcal{T}^{\text{PI}}$  that also contains *two* sub-populations of traders,  $\mathcal{T}_1^{\text{PI}}$  and  $\mathcal{T}_2^{\text{PI}}$ . Again, each trader  $a_i$  is a member of exactly one of the sub-populations, thus:

$$\mathcal{T}^{\text{PI}} = \{a_i : (a_i \in \mathcal{T}_1^{\text{PI}}) \oplus (a_i \in \mathcal{T}_2^{\text{PI}})\} \quad (5.15)$$

All traders have the following constraints:

$$\begin{aligned} \forall a_i \in \mathcal{T}^{\text{PI}}, \quad \mathbf{r}_i^{a_i} &= \langle 1.0, 1.0 \rangle \\ \forall a_i \in \mathcal{B} \cap \mathcal{T}^{\text{PI}}, \quad \mathbf{r}_i^{a_i} &= \langle 0.2, 0.2 \rangle \\ \forall a_i \in \mathcal{S} \cap \mathcal{T}^{\text{PI}}, \quad \mathbf{r}_i^{a_i} &= \langle 0.0, 0.0 \rangle \end{aligned} \quad (5.16)$$

though *both* the buyers and sellers of the two sub-populations have different *preferences*:

$$\begin{aligned} \forall a_i \in \mathcal{T}_1^{\text{PI}}, \quad \mathbf{w}^{a_i} &= \langle 0.7, 0.3 \rangle \\ \forall a_i \in \mathcal{T}_2^{\text{PI}}, \quad \mathbf{w}^{a_i} &= \langle 0.3, 0.7 \rangle \end{aligned} \quad (5.17)$$

With a lack of trader constraints within both populations, all resource types could be considered within traders’ consideration sets. Preferences over the two resource attributes will mean that, in general, a buyer  $a_i \in \mathcal{B} \cap \mathcal{T}_1^{\text{PI}}$  would prefer to trade with a seller  $a_i \in \mathcal{S} \cap \mathcal{T}_2^{\text{PI}}$ , and vice versa, because the respective sellers can produce more of the attributes buyers’ prefer, for less cost. The magnitude of preference weights only affects the height of the niches, rather than their position, thus the attributes’ values are not as important as their inequality.

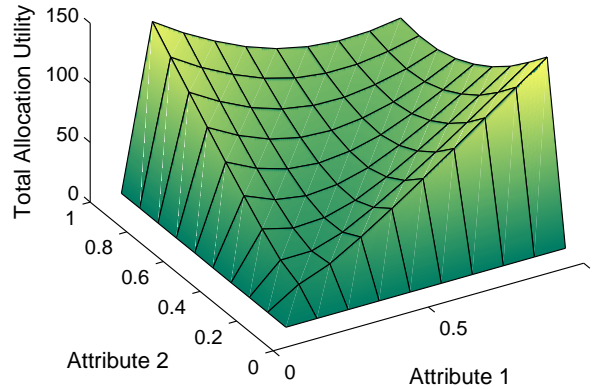


Figure 5.4: Maximum theoretical daily total trader profit for a randomly generated *preference-induced niches* trader context. There are two well-defined niches within the landscape. At one niche, buyers from sub-population  $\mathcal{T}_1^{\text{PI}}$ , i.e., those who prefer attribute one to attribute two, prefer to trade with sellers from sub-population  $\mathcal{T}_2^{\text{PI}}$ , because they can provide attribute one for a lower cost than attribute two. The preferred resource type at this niche is  $\pi = \langle 1.0, 0.2 \rangle$ . A second niche exists where the preferred resource type is  $\pi = \langle 0.2, 1.0 \rangle$ . Within this niche, buyers from the second sub-population  $\mathcal{T}_2^{\text{PI}}$  prefer the second resource attribute, and sellers from sub-population  $\mathcal{T}_2^{\text{PI}}$  can produce it for less than resource attribute one. Overall trader profit is maximised when two separate markets exist for the two resource types specified. Thus, the two market niches require at least two market-exchanges to provide markets.

### 5.3.2 Possible charging contexts

Market-exchanges are unaware of the market niches *a priori*, because they do not have access to the global supply and demand schedules, or the preferences and constraints of traders. Markets for resource types preferred by market niches are likely to be more attractive to traders, and lead to larger volumes of trades. Thus, while technically an assumption and not guaranteed, satisfying a market niche is likely to result in increased revenue for market-exchanges. Information asymmetries between exchanges and traders seed the difficulties that market-exchanges face when attempting to maximise profits through the selection of the attribute-levels of their market's resource type.

While an exchange searches for market niches by sampling the

### 5.3. DEFINING ENVIRONMENTAL CONTEXTS

attribute-level space with its ALS strategy, the revenue received from sampling a point is influenced not only by that point's location, but also by the charging scheme used to generate that revenue. Further, Figures 5.1–5.4 show total *trader profits* at each point, which is private information, and market-exchanges can only glean that information by learning, using their profit signals. Therefore, the exact charging scheme and fee structure used by an exchange is important, and so three different *charging contexts*, based on the charging structures defined in Section 4.1.1 (Page 85), are considered. Rather than using combinations of different charges, which may confound the impact each of the fee types has, they are isolated.

#### **'Registration fee' charging context**

The *registration fee* charging context involves market-exchanges applying only registration fees to traders who join their markets. Recall that a registration fee is a flat-fee, i.e., the same level applies to all traders, and it is applied at the beginning of each trading day. When this charging context is used traders may end a trading day with a net loss if they are unable to successfully trade. One potential problem with discovering market niches when this charging context is in use, is that the maximum revenue available at each point in the attribute-level space is determined only how many traders would be willing to trade the resource type at that point. Thus, revenue from points near market niches may be the same as revenue from market niches themselves, even though traders would prefer the market niche rather than points near it.

#### **'Transaction price fee' charging context**

Unlike the *registration fee* charging context, when the *transaction price fee* charging context is in use, exchanges do not charge traders to join their market. However, for each trade executed by the market exchange, both traders involved pay a fixed portion of the transaction price of their trade. Therefore, the revenue a

market-exchange receives when using this context monotonically increases with the number of trades it is able to execute in its market. Because, in comparison to other points in the attribute-space, markets occupying market niches are expected to have a high volume of trades, it is hypothesised that exchanges using this charging context will be better able to discover market niches.

#### ‘Bid/Ask spread commission’ charging context

The final charging context consider is the *bid/ask spread commission* charging context. When this context is in use by exchanges, traders are free to join markets without cost, however, a portion of the difference between the trader’s offer into the market, and the resulting transaction price, is charged by the exchange. The difference between a matching buyer and seller’s bid and ask price is known as the *spread*. For example, given a bid  $\rho_b = 20$  and an ask  $\rho_a = 10$ , a market-exchange, using the  $k = 0.5$  *k-pricing* policy [150] would set the resulting transaction price  $\tau = 15$ . Each trader would then be charged a proportion of the difference between their bid:  $\rho_b - \tau$ , or ask:  $\tau - \rho_a$ .

Typically, the revenue generated from this charging scheme is better at points in the attribute-level space where more trades can occur, however, revenue is also affected by the trading strategy in use by the traders. The more efficient the traders are in converging on the competitive equilibrium price, the *tighter* the spread gets. In a completely efficient market, where all traders were shouting the equilibrium price, the *bid/ask spread commission* charging context would generate no revenue, regardless of whether a market niche was being occupied, because all offers shouted would be equivalent to the transaction prices.

## 5.4 Attribute-level Selection Strategy Performance

Within this section, the performance of the *attribute-level selection* (ALS) strategies discussed in Section 5.2 is empirically analysed, via simulations using

#### 5.4. ATTRIBUTE-LEVEL SELECTION STRATEGY PERFORMANCE

instantiations of the environmental contexts proposed in the previous section. Performance is measured in two ways: (i) a quantitative measure of performance, based upon the overall profit that a market-exchange can generate using each ALS strategy; and (ii) a qualitative measure of relative performance, based upon bilateral rankings. The main overarching research question addressed within this section is:

*How are candidate attribute-level selection strategies' performance properties affected across different environmental situations, and can any be seen to generalise across all the environments?*

In order to make a step towards answering this question, the most basic of scenarios that still allowed for meaningful analysis was considered. Specifically, by only considering *bilateral* simulations, where two market-exchanges compete against each other, it is possible to exhaustively evaluate all representative environmental contexts, where, from the perspective of a market-exchange using an ALS strategy, an environmental context consists of: (i) a competing ALS strategy being used by another market-exchange (competitor context); (ii) a representative trading context; and (iii) a representative charging context. This methodology follows in the spirit of the novel methodology first presented Chapter 3 for measuring the generalisation ability of market-mechanisms. Further, it is noted that bilateral simulation of similar double-auction mechanisms has been used an approach by other researchers, e.g., Niu et al. [116], to analyse the sensitivity of each mechanism to the presence of another. Within the analysis carried out in the rest of this section, specific attention is given to the following:

- The presence of competing strategies on the performance of ALS strategies;
- The impact of charging context on the performance of ALS strategies;
- The impact of trader context on the performance of ALS strategies.

which will hopefully allow the following hypotheses to be addressed:

**Hypothesis 5.1.** *It is likely that the performance of ALS strategies will be sensitive to at least some environmental contexts, because of the complex, adaptive nature of the system. Therefore no strategies will generalise well over all contexts.*

**Hypothesis 5.2.** *Each simulation uses a specific static environmental context, with well-defined trader niches and non-adaptive charging schemes in place. Therefore, out of the bandit strategies,  $\epsilon$ -decreasing should perform the best.*

### 5.4.1 Experimental setup

In order to answer the research questions and hypotheses posed, the following general experimental setup is used. Firstly, while all ALS strategies (competitor contexts) and charging contexts are considered, only simulations involving the *unconstrained single niche* and *constrained single niche* trader contexts, are used. Justifications for this are as follows: (i) reducing the environmental dynamics allows for a clearer understanding of how environmental factors impact ALS strategies; (ii) enforcing competition over a *single niche*—thus excluding cooperative equilibria outcomes—makes it clearer to see which ALS strategies can find niches faster and hold on to them. Given this, *self-play* simulations, where both exchanges use the same ALS strategy are excluded because, in these cases, expected performance is identical. The trading population used in each trading context comprises 300 ZIP traders, as described in Section 4.4.1 (Page 103), and is composed of an equal number of buyers and sellers. The charging context used is applied to both market-exchanges and remains in use for all of the simulation, which allows the impact of both competing ALS strategies and charging context to be analysed independently of each other.

Each simulation lasts for 5000 trading days. At the beginning of each trading day both the market-exchanges, in accordance with their ALS strategies, set the attribute-levels of the resource to be traded within their respective markets. Traders then join a market and begin to trade. Based upon the charging scheme in use, each market-exchange generates some revenue, or *profit*, for that

#### 5.4. ATTRIBUTE-LEVEL SELECTION STRATEGY PERFORMANCE

trading day, which is used by their ALS strategies to help select the resource type to be traded the next trading day.

##### Quantitative performance measure

Market-exchange  $m_k$ 's profit is generated at the end of each trading day  $t$  according to Equation 4.2.2 on Page 90. As a measure of performance over an entire simulation (5000 days), the *market-exchange simulation profit* is used, which is simply the mean profit generated over all days.

$$P_{m_k}^{sim} = \frac{1}{n} \sum_{t=1}^n r_{m_k}^t, \quad (5.18)$$

where  $P_{m_k}^{sim}$  is  $m_k$ 's simulation profit for simulation  $sim$ , which lasted  $n$  trading days.  $r_{m_k}^t$  refers to the profit  $m_k$  received on day  $t$ .

##### Qualitative performance measure

As discussed in Chapter 3, comparing only quantitative performance across different environmental contexts is not always useful, because environmental changes can unfairly alter attainable profits. One approach to this issue might be to use a normalised measure of profit, such as the profit share. However, statistical analysis becomes difficult, as normalising performance in this way confounds the results. For example, if one strategy is particularly negatively influenced by a change in environment, that would automatically inflate the score of any of its opponents, even if they themselves do not strictly perform better in the changed environment. Instead, so that the relative performance of ALS strategies between contexts can be qualitatively compared, the number of simulation *wins* is recorded for market-exchanges using each strategy. For example, given two market-exchanges using different ALS strategies,  $m_1$  and  $m_2$ ,



as well as a simulation  $sim$ , a ‘win’ is awarded to  $m_1$  accordingly:

$$\text{win}(m_1, m_2, sim) = \begin{cases} 1 & \text{if } P_{m_1}^{sim} \geq P_{m_2}^{sim} \\ 0 & \text{if } P_{m_1}^{sim} < P_{m_2}^{sim}, \end{cases} \quad (5.19)$$

$m_1$  is awarded the win in the event of a draw, but given results are in the form of real-valued numbers, few is any draws were observed.

### 5.4.2 Results and analysis

The simulation methodology for the following experiments is as follows. Each simulation is repeated 50 times, so the mean of the 50 market-exchange simulation profit values (Equation 5.18) are reported, along with standard deviation values. A large number of simulation repetitions provides good sample sizes for running appropriate statistical tests.

The market-based model within this thesis leads to complex interactions between agents, and it is unwise to assume that data samples will be normally distributed. To overcome this assumption rigorous statistical analysis is used. To test for normality, all data samples are subjected to the *Lilliefors Test* [95], a goodness of fit test for the Normal distribution. If the null hypothesis of this test (that the data is normally distributed) is rejected, then all reported test statistics for that sample are provided by the non-parametric *Wilcoxon Signed-rank Test* [180]. In the case of normality, equality of sample means is tested using the *paired sample T-Test*.

Each simulation used the default parameters in Table 5.1. For each of the 50 simulation repetitions, budget constraints were randomly generated for all traders, along with a new *random seed* for the simulation. Given the six ALS strategies, three charging contexts, and two trader contexts, the next two sections report and analyse results from some  $(6 - 1)^2 \times 3 \times 2 = 150$  different

#### 5.4. ATTRIBUTE-LEVEL SELECTION STRATEGY PERFORMANCE

Agent	Description	Parameter Details
Traders	Budget Constraint	$\lambda_{a_i} = N(6, 0.7)$
	Market-Selection Strategy	Page 108
	Trading Strategy	ZIP algorithm details: Page 103
Market-exchanges	Double-Auction Settings	Page 100
	Charges & Fees (Page 85)	Registration fee, $\zeta_{m_k}^{reg} = 0.01$ Transaction tax fee, $\zeta_{m_k}^{tra} = 1\%$ Bid/Ask fee, $\zeta_{m_k}^{com} = 100\%$
	<i><math>\epsilon</math>-greedy ALS</i>	$\epsilon = 0.1$
	<i><math>\epsilon</math>-decreasing ALS</i>	$\delta = 15$
	<i>Softmax ALS</i>	$\tau = 0.3$
	<i>Rank-based ALS</i>	$\zeta = 30$
	<i>1+1 ES ALS</i>	$\sigma = 0.12$
	EA ALS	$\sigma = 0.12$ $p = 10$

Table 5.1: Default parameters used in all simulations unless otherwise stated within the text. All parameters remain fixed for the duration of each simulation. All parameters, with the exception of budget constraints remain constant over *all* simulations. Every simulation, all budget constraints are randomly distributed according to the Normal distribution specified, but are bounded within the range  $\lambda_{a_i} \in [2, 10]$ . Specific parameter settings were justified as follows:  $\epsilon = 0.1$  is a common choice, and empirically found to be near-optimal for generally short numbers of plays [164, p. 29];  $\delta = 15$  was chosen as it gives  *$\epsilon$ -decreasing* about 1/3 of the simulation’s time to explore, before *almost surely* behaving greedily;  $\tau = 0.3$  was selected based upon initial testing using various simulations;  $\zeta = 30$  was chosen because, based on there being 25 possible action ranks, it would behave greedily only 75% of the time, but choose from the best three actions with  $\approx 95\%$  probability;  $\sigma = 0.12$  was chosen for *1+1 ES ALS* and *EA ALS* because it equates to their being  $\approx 10\%$  of mutating an attribute by at least much as a bandit strategy changing action does, i.e., 10% of mutations would be equivalent to a bandit strategy choosing a new action. For the *EA ALS*, a population size of 10 was chosen, which gave the best results from some initial exploratory simulations.

	$\varepsilon$ -dec	$\varepsilon$ -gre	EA	1+1 ES	Rank	Softmax
$\varepsilon$ -dec		0.346 (316.0)	<b>0.499</b> (8.7)	<b>0.511</b> (209.0)	<b>0.466</b> (5.9)	<b>0.488</b> (44.1)
$\varepsilon$ -gre	<b>0.447</b> (3.5)		<b>0.501</b> (12.4)	<b>0.525</b> (147.0)	<b>0.496</b> (7.2)	<b>0.466</b> (38.8)
EA	0.305 (85.0)	0.269 (54.0)		0.350 0.41 (0.8)	0.287 (33.0)	<b>0.345</b> (5.2)
1+1 ES	0.312 (209.0)	0.292 (147.0)	0.312 0.29 (506)		0.313 0.02 (2.5)	0.239 0.01 (2.7)
Rank	0.372 (-5.9)	0.365 (-7.2)	<b>0.490</b> (12.3)	0.215 0.03 (413)		<b>0.475</b> (11.2)
Softmax	0.203 (-44.1)	0.177 (-38.8)	0.261 (-5.2)	0.171 0.01 (-2.7)	0.293 (-11.2)	

Table 5.2: Mean *simulation profit* over 50 simulation repetitions for market-exchanges using various ALS strategies, when the environmental context comprises the *bid/ask spread commission* charging and *unconstrained single niche* trader, contexts. The top value in each cell are the mean simulation profits for the ALS strategy in the respective *row* against the ALS strategy in the respective *column*. Emboldened profits indicate they are greater than their competitor’s *and* they come from statistically distinct samples. *T-values* are shown in parentheses under each profit value; an emphasised *t-value* indicated the samples were tested using the non-parametric statistical test. *P-values*  $\leq 0.005$  are omitted, otherwise they are shown to the left of *t-values*.

environmental contexts<sup>1</sup>.

### Unconstrained single niche performance

All simulations within this section involved the *unconstrained single niche* trader context. In each simulation, the market-exchanges were competing over a single population of traders who preferred to trade resources  $\pi = \langle 1.0, 1.0 \rangle$ , viz, there was a single market niche (Figure 5.1). Results are sectioned into three tables (Tables 5.2–5.4), with each table representing a separate charging context. Values in each table indicate the mean market-exchange simulation profit from 50 repetitions of the simulation in that cell. Table 5.2 displays results for simulations that took place when the *bid/ask spread commission* charging context was used by

<sup>1</sup>In order to repeat each simulation 50 times, some 7,500 simulation instances were executed. Each simulation took between 20–45 minutes of wall-clock time, running on a single core of a Quad Core Xeon CPU (2.33Ghz, 8Mb L2 cache) located on a computational grid infrastructure.

#### 5.4. ATTRIBUTE-LEVEL SELECTION STRATEGY PERFORMANCE

the market-exchanges. Immediately of note is that within this environmental context,  $\epsilon$ -greedy, arguably the simplest of all the attribute-level selection strategies, outperforms all others. This claim is supported with  $p$ -values  $\leq 0.005$  for each statistical test involving  $\epsilon$ -greedy.  $\epsilon$ -decreasing also performs very well, significantly outperforming all of the other except  $\epsilon$ -greedy.

Figure 5.5 provides a closer look at the distribution of profits made by  $\epsilon$ -greedy and  $\epsilon$ -decreasing, for all of their simulations against each other. Both strategies have non-zero lower bounds on their profit, indicating they both always found profitable parts of the attribute-level space, however,  $\epsilon$ -decreasing ends up closer to the lower bound in the majority of the simulations.

On examination of the *market-share*—a measure of how many traders were attracted on average to each market—that each market-exchange using the strategies achieved over a simulation, the following results are discovered.  $\epsilon$ -greedy achieved a mean market-share of  $61.2\% \pm 15.3$  in all simulations against  $\epsilon$ -decreasing, which only achieved  $38.8\% \pm 15.3$ ; a paired t-test of equality of means returns a  $p$ -value  $< 0.005$ . Thus, while  $\epsilon$ -decreasing finds the same profitable parts of the space as  $\epsilon$ -greedy, its early exploration lead it to lose market-share for the rest of the simulation. Figure 5.5 also provides an example of how data within the model can be non-normally distributed, thus only running tests relying on that assumption would be inappropriate.<sup>2</sup> In Table 5.3, displays results for simulations that took place when the *registration fee* charging context was used by the market-exchanges. Contrary to when the *bid/ask spread commission* charging context is place,  $\epsilon$ -greedy fails to statistically outperform  $\epsilon$ -decreasing. While  $\epsilon$ -greedy significantly outperforms all others, the  $p$ -values for a paired *T-Test* of equality of means between the  $\epsilon$ -greedy and  $\epsilon$ -decreasing samples, results in a  $t$ -value of 0.35—too large to be considered significant. Therefore, performance is equitable. At this point, it is clear strategies other than  $\epsilon$ -greedy or  $\epsilon$ -decreasing don't appear to be performing to the same standard, within the two charging

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<sup>2</sup>In this case, Lilliefors' composite goodness-of-fit test reports a  $p$ -value  $\leq 0.001$  and a  $k$ -value of 0.185 for  $\epsilon$ -decreasing's sample distribution in Figure 5.5

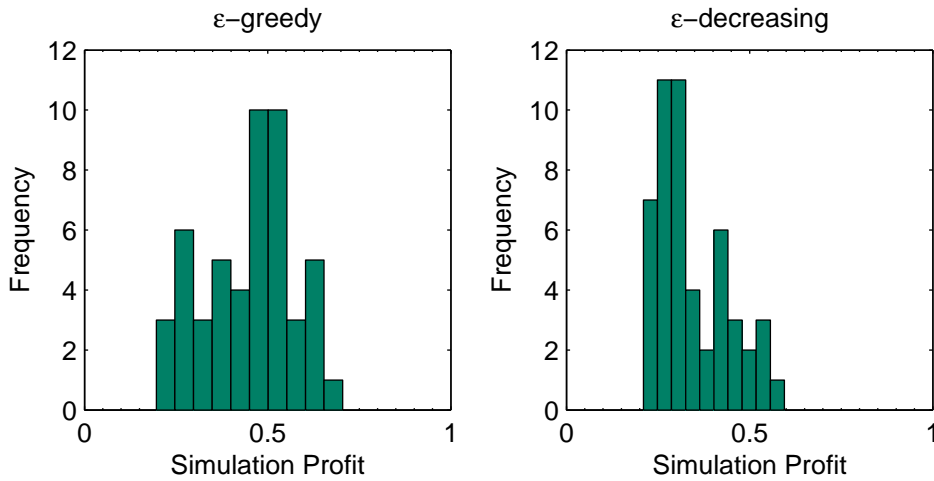


Figure 5.5: Simulation profit distributions for market-exchanges using the  $\epsilon$ -greedy ALS strategy (left) or the  $\epsilon$ -decreasing strategy (right), when in competition, and using the *bid/ask spread commission* charging context. While profits are normally distributed when using  $\epsilon$ -greedy, they are not when using  $\epsilon$ -decreasing.

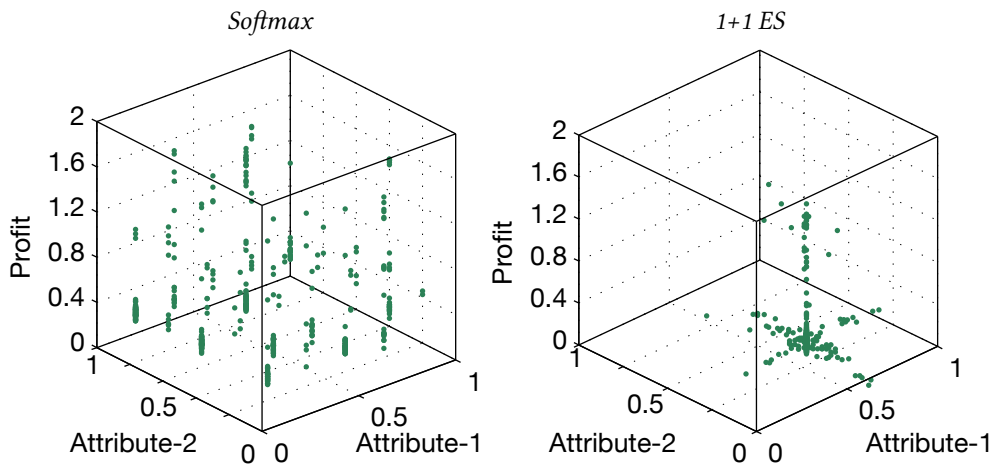


Figure 5.6: Typical behaviour of *Softmax* (left) and *1+1 ES* (right) attribute-level selection strategies when involved in simulations using the *Unconstrained Single Niche* trader and *Market Registration Fee* charging, contexts, against each other. Each point represents a trading day: the  $x$  and  $y$  axes indicate the attribute-levels chosen for that day, and the  $z$  axis indicates the profit attained for that attribute-level choice. The *Softmax* strategy appears to be choosing points with almost uniform probability, indicating its temperature  $\tau$  setting is too high for this particular environmental context. *1+1 ES* performs better in this case, but it is likely even more profit could be achieved if its attribute-level choice focussed around  $\pi = \langle 1.0, 1.0 \rangle$ . 500 sequential data points are shown from a randomly chosen section of a typical simulation.

context considered so far. For example, it appears that because the rewards, i.e., profits, are relatively equal for different points in the attribute-level space the

#### 5.4. ATTRIBUTE-LEVEL SELECTION STRATEGY PERFORMANCE

	$\varepsilon$ -dec	$\varepsilon$ -gre	EA	1+1 ES	Rank	Softmax
$\varepsilon$ -dec		0.834 0.35 (-1.0)	<b>1.297</b> (26.0)	<b>1.117</b> (262.0)	<b>1.010</b> (8.5)	<b>1.341</b> (67.8)
$\varepsilon$ -gre	0.894 0.35 (1.0)		<b>1.298</b> (15.6)	<b>1.117</b> (282.0)	<b>1.067</b> (9.7)	<b>1.372</b> (47.1)
EA	0.453 (26.0)	0.424 (-15.6)		0.658 (331.5)	0.618 (-6.8)	<b>1.149</b> (35.0)
1+1 ES	0.618 (262.0)	0.607 (282.0)	<b>1.049</b> (331.5)		0.754 0.21 (506)	<b>1.181</b> (216.0)
Rank	0.702 (-8.5)	0.665 (-9.7)	<b>1.123</b> (6.8)	0.934 0.21 (506)		<b>1.154</b> (8.6)
Softmax	0.386 (-67.8)	0.363 (-47.1)	0.596 (35.0)	0.522 (216.0)	0.583 (79.0)	

Table 5.3: Mean *simulation profit* over 50 simulation repetitions for market-exchanges using various ALS strategies, when the environmental context comprises the *registration fee* charging and *unconstrained single niche* trader, contexts. For assistance in interpreting the results, see the caption for Table 5.2

*Softmax* ALS strategy, as show in Figure 5.6, will select between all points with almost equal probability, highlighting the sensitivity of its temperature setting  $\tau$  to the environmental context. While the *1+1 ES* ALS strategy significantly outperforms the *Softmax* ALS strategy, because, as shown in Figure 5.6, it is able to converge on a profitable parts of the attribute-level space, it is unable to compete with  $\varepsilon$ -greedy or  $\varepsilon$ -decreasing. Again, based upon simulation data this appear to be due to it being too slow to find the optimal point in the attribute-level space, and thus being unable to attract traders *away* from its competitor. Table 5.4 displays the results for simulations that took place when the *transaction fee* charging context was in place. As with the previous two charging contexts,  $\varepsilon$ -greedy failed to be convincingly outperformed by any of the other attribute-level selection strategies. However, it does not *dominate* all strategies; for example, it does not statistically outperform *Softmax* or *1+1 ES*, indicating either an improvement in the performance of those two strategies within this charging context, or a decline in  $\varepsilon$ -greedy. Figure 5.7 supports the argument that *Softmax* and *1+1 ES* actually improve in this charging context, rather than  $\varepsilon$ -greedy declining. Notice that, unlike the *registration fee* context (Figure 5.6),

both *Softmax* and *1+1 ES* find the most profitable part of the space. Overall

	$\varepsilon$ -dec	$\varepsilon$ -gre	EA	1+1 ES	Rank	Softmax
$\varepsilon$ -dec		3.568 0.42 (−0.8)	5.579 (15.8)	2.920 0.12 (476)	4.895 (18.0)	3.604 0.54 (574)
$\varepsilon$ -gre	3.766 0.42 (0.8)		5.413 (11.7)	3.814 0.76 (605)	5.015 (12.8)	3.970 0.73 (601)
EA	1.328 (1.0)	1.484 (−11.7)		1.945 (191.0)	2.769 (−2.9)	0.638 (0.0)
1+1 ES	4.657 0.12 (476)	3.464 0.75 (605)	4.994 (191.0)		4.387 0.55 (575)	2.215 0.22 (510)
Rank	2.367 (−18.0)	2.188 (−12.8)	3.640 (2.9)	3.335 0.55 (575)		3.415 0.28 (525)
Softmax	3.843 0.54 (574)	3.460 0.73 (601)	5.892 (25.6)	4.464 0.22 (510)	2.963 0.16 (−1.4)	

Table 5.4: Mean *simulation profit* over 50 simulation repetitions for market-exchanges using various ALS strategies, when the environmental context comprises the *transaction fee* charging and *unconstrained single niche* trader, contexts. For assistance in interpreting the results, see the caption for Table 5.2

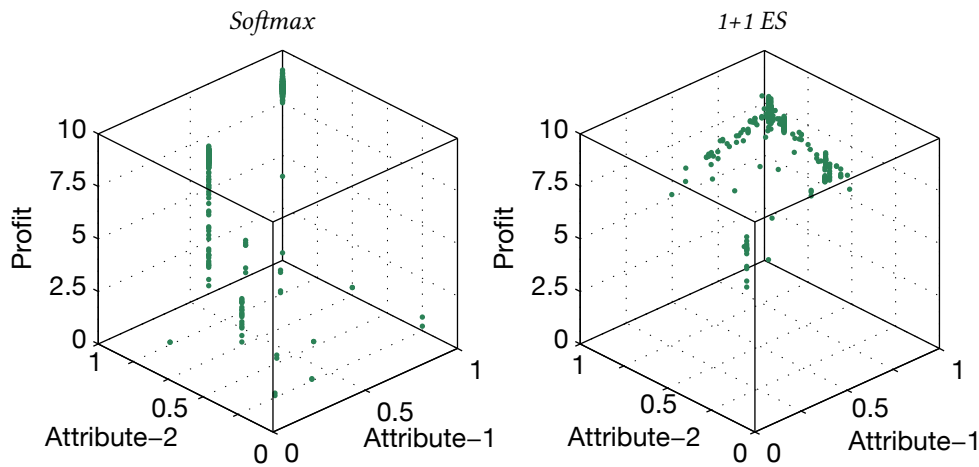


Figure 5.7: Typical behaviour of *Softmax* (left) and *1+1 ES* (right) attribute-level selection strategies when involved in simulations using the *unconstrained Single Niche* trader and *transaction fee* charging, contexts, against each other. Each point represents a trading day: the  $x$  and  $y$  axes indicate the attribute-levels chosen for that day, and the  $z$  axis indicates the profit attained for that attribute-level choice. In contrast with simulations using the *registration fee* charging context (Figure 5.6), the *Softmax* strategy performs much better, focussing on several good points in the space, indicating its temperature setting is more appropriate for this environment. Of further interest is that *1+1 ES* also performs better, converging correctly on the most profitable part of the attribute-level space,  $\pi = \langle 1.0, 1.0 \rangle$ . 500 sequential data points are shown from a random section of a typical simulation.

#### 5.4. ATTRIBUTE-LEVEL SELECTION STRATEGY PERFORMANCE

performance results for ALS strategies are more equitable within the *transaction fee* charging context. And, supported by data such as that provided in Figure 5.7, many of ALS strategies can locate the most profitable part of the attribute-level space, which is also the market niche, indicating the *transaction fee* charging context may be best for finding the market niche within this trader context.

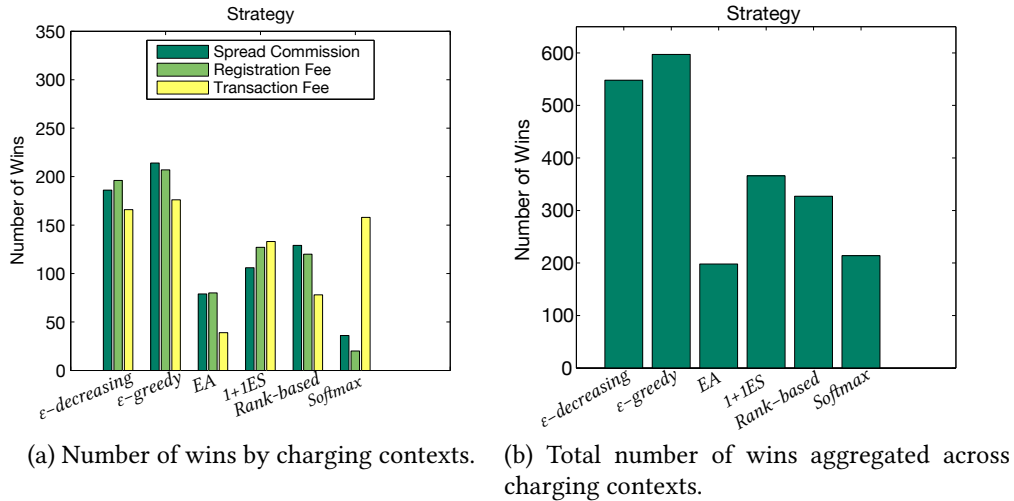


Figure 5.8: The number of wins managed by each of the attribute-level selection strategies for the *unconstrained single niche* trader context. (a) Wins are separated according to charging context. Each strategy plays the five others 50 times, therefore a maximum score for a charging context would be 250. (b) All wins aggregated across the three charging contexts. Note that the more dynamic bandit strategy,  $\epsilon$ -greedy outperforms  $\epsilon$ -decreasing.

Finally for the *unconstrained single niche* trader context, ALS strategies are analysed *across* all charging and competitor contexts, using the qualitative performance metric outlined in Section 5.4.1. Using the *win* metric (Equation 5.19) the number of wins for each ALS strategy are aggregated and presented in Figure 5.8. Two representations of the number of are visualised. In Figure 5.8a, which separates the wins by charging context, it becomes clear just how much of an impact the charging context has on the performance of strategies. For example, *Softmax*, whose temperature was chosen experimentally via a simulation where the *transaction fee* context was in place, has a serious sensitivity to other charging contexts, due in part to its success being *reliant* on



the *absolute* profits an action returns, rather than the *relative* differences between actions' profits. Total wins over all contexts are shown in Figure 5.8b.

### Constrained single niche performance

This part of the section follows an identical methodology to the previous section, with the exception that the *constrained single niche* trader context is used for all simulations. Recall that buyers in the *constrained single niche* trader context population have maximum constraints on attribute-levels, and thus the market niches exists at a point other than  $\pi = \langle 1.0, 1.0 \rangle$ . It is certainly true that the *unconstrained single niche* and *constrained single niche* trader contexts are similar in that they both have a single niche, and no traders have preferences. However, the subtle difference of buyers having maximum constraints may make significantly impact the performance of some ALS strategies because significant parts of the attribute-level space are going to be undesirable to buyers. Apart from using the *constrained single niche* trader context, simulation detail are identical to the previous set.

Results for the *bid/ask spread commission* charging context are shown in Table 5.5. While general performance for the ALS strategies is similar in most cases, there are some interesting observations. Firstly, in comparison to the *unconstrained single niche* simulations, reported in Table 5.2 on Page 150,  $\epsilon$ -greedy is no longer statistically better than  $\epsilon$ -decreasing. An intuitive explanation for this may lie in this trader context having more *unforgiving* points in the attribute-level space, where, if chosen, will result in buyers being unable to trade—thus lower market-exchange profits—because buyers' valuations don't meet sellers' costs for that resource type. The fact that  $\epsilon$ -decreasing's total mean profit only reduced by 40.3% between the two trader contexts, while  $\epsilon$ -greedy's reduced by 49.2% supports this hypothesis. In Table 5.6, results of simulations involving the *registration fee* trader context are presented. While maximum constraints hinder a buyer's ability to trade resource types above its constraints

#### 5.4. ATTRIBUTE-LEVEL SELECTION STRATEGY PERFORMANCE

	$\epsilon$ -dec	$\epsilon$ -gre	EA	1+1 ES	Rank	Softmax
$\epsilon$ -dec		0.206 0.99 (0.0)	<b>0.302</b> (26.4)	<b>0.259</b> (8.7)	<b>0.309</b> (34)	<b>0.303</b> (62)
$\epsilon$ -gre	0.205 0.82 (590)		<b>0.255</b> (16.0)	<b>0.220</b> (6.4)	<b>0.283</b> (15)	<b>0.273</b> (34)
EA	0.056 (0.0)	0.049 (0.0)		0.060 0.02 (-2.4)	0.099 (-3.4)	0.101 0.07 (1.8)
1+1 ES	0.090 (69.0)	0.098 (135)	0.107 0.04 (422)		0.089 0.9 (404)	<b>0.128</b> (215)
Rank	0.151 (-34.3)	0.141 (-15.9)	<b>0.146</b> (325)	0.094 0.9 (404)		<b>0.124</b> (291)
Softmax	0.036 (-62.4)	0.025 (-34.3)	0.079 0.07 (-1.8)	0.042 (-4.9)	0.084 (-3.6)	

Table 5.5: Mean *simulation profit* over 50 simulation repetitions for market-exchanges using various ALS strategies, when the environmental context comprises the *bid/ask spread commission* charging and *constrained single niche* trader, contexts. Results are similar the same set of simulations using the *unconstrained single niche* trader context in Table 5.2, however,  $\epsilon$ -greedy has lost its statistically significant winning edge against  $\epsilon$ -decreasing. Further, *Softmax* is particularly sensitive to this trader context versus the *unconstrained single niche* context—its overall mean profit (summed across its row) reduced by 75.9%, in comparison to the best strategy ( $\epsilon$ -greedy), whose equivalent profits only reduced by 49.2%. For assistance in interpreting the results, see the caption for Table 5.2 on Page 150.

(where its valuation doesn't meet a sellers increased costs), it is not prevented from *joining* said market; it will just have a hard time trading. It is therefore interesting to note that unlike the previous *bid/ask spread commission* charging context, where  $\epsilon$ -greedy now statistically outperforms  $\epsilon$ -decreasing—there are fewer *unforgiving* parts of the attribute-level space when you only need traders to join your market, rather than successfully trade in it. In Table 5.7, results of simulations involving the *transaction price fee* trader context are shown, and further interesting results emerge. For example, it is the first case where  $\epsilon$ -greedy loses to any strategy (*Softmax*) other than  $\epsilon$ -decreasing; indeed even  $\epsilon$ -decreasing is unable to statistically beat *Softmax*, suggesting that *Softmax*'s configuration is suited to this particular environment.

Finally, in Figure 5.9 the number of simulation wins is shown for each strategy. Overall  $\epsilon$ -decreasing performs best in this context. Given that this trader

	$\varepsilon$ -dec	$\varepsilon$ -gre	EA	1+1 ES	Rank	Softmax
$\varepsilon$ -dec		0.704 0.01 (-2.7)	<b>1.329</b> (0.0)	<b>1.120</b> (7.4)	<b>1.096</b> (14.7)	<b>1.310</b> (67.5)
$\varepsilon$ -gre	<b>0.916</b> 0.01 (2.7)		<b>1.361</b> (35.9)	<b>1.029</b> (274)	<b>1.125</b> (12.7)	<b>1.372</b> (40.0)
EA	0.232 (0.0)	0.201 (-35.9)		0.523 0.07 (451)	0.421 (-11.5)	<b>0.625</b> (3.1)
1+1 ES	0.461 (109)	0.543 (274)	0.753 0.07 (451)		0.764 0.36 (543)	<b>0.962</b> (136)
Rank	0.496 (-14.7)	0.496 (-12.7)	<b>1.006</b> (11.5)	0.668 0.36 (543)		<b>1.089</b> (12.4)
Softmax	0.260 (-67.5)	0.197 (-40.0)	0.438 (-3.1)	0.287 (136.0)	0.345 (-12.4)	

Table 5.6: Mean *simulation profit* over 50 simulation repetitions for market-exchanges using various ALS strategies, when the environmental context comprises the *registration fee* charging and *constrained single niche* trader, contexts. Results are in general similar the same set of simulations using the *unconstrained single niche* trader context in Table 5.3, however, in this trader context  $\varepsilon$ -greedy statistically outperforms  $\varepsilon$ -decreasing. For assistance in interpreting the results, see the caption for Table 5.2, on Page 150.

	$\varepsilon$ -dec	$\varepsilon$ -gre	EA	1+1 ES	Rank	Softmax
$\varepsilon$ -dec		<b>2.477</b> (4.4)	<b>3.585</b> (36.3)	<b>3.157</b> (114.0)	<b>3.527</b> (26.1)	1.878 0.02 (400)
$\varepsilon$ -gre	1.720 (-4.4)		<b>3.449</b> (22.3)	<b>3.111</b> (104)	<b>3.256</b> (16.9)	1.529 (322)
EA	0.292 (0.0)	0.252 (0.0)		0.449 (177.0)	0.642 (335.0)	0.053 (0.0)
1+1 ES	1.027 (114.0)	0.831 (104.0)	<b>2.358</b> (177.0)		<b>1.932</b> 0.2 (331)	0.645 (102.0)
Rank	0.444 (0.0)	0.435 (3.0)	<b>1.239</b> (335.0)	1.365 0.2 (331)		<b>1.326</b> (298.0)
Softmax	2.586 0.02 (400)	<b>2.722</b> (3.4)	<b>3.634</b> (33.9)	<b>3.442</b> (102.0)	0.637 (298.0)	

Table 5.7: Mean *simulation profit* over 50 simulation repetitions for market-exchanges using various ALS strategies, when the environmental context comprises the *transaction fee* charging and *constrained single niche* trader, contexts. Results differ somewhat from the *unconstrained single niche* trader context results in Table 5.4. Both  $\varepsilon$ -decreasing and *Softmax* see significant improvements over the *unconstrained single niche* case. For assistance in interpreting the results, see the caption for Table 5.2, on Page 150.

context contains buyer maximum constraints, there are more points in the attribute-level space that result in lower numbers of feasible transactions, which

#### 5.4. ATTRIBUTE-LEVEL SELECTION STRATEGY PERFORMANCE

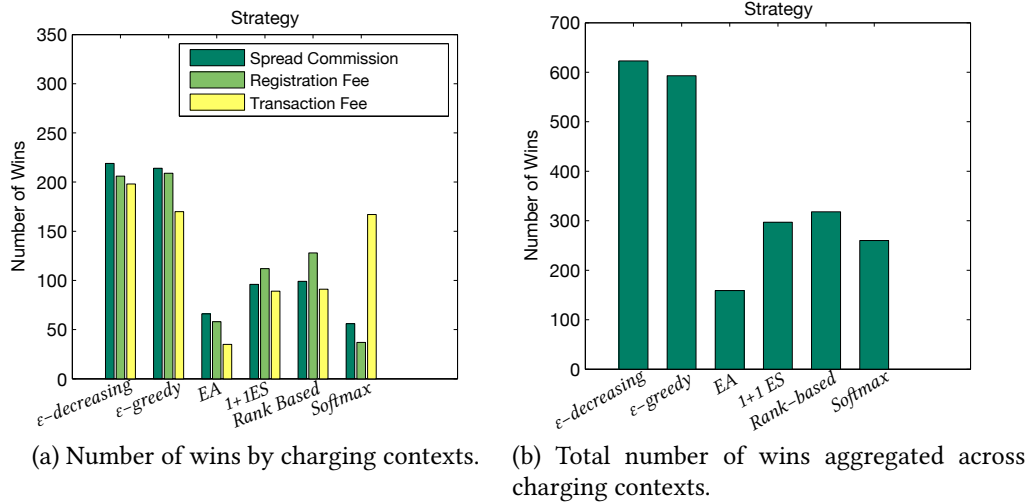


Figure 5.9: The number of wins managed by each of the attribute-level selection strategies for the *constrained single niche* trader context. (a) Wins are separated according to charging context. Each strategy plays the five others 50 times, therefore a maximum score for a charging context would be 250. (b) All wins aggregated across the three charging contexts. Compared to the equivalent data for the *unconstrained single niche* (Figure 5.8)  $\epsilon$ -decreasing outperforms  $\epsilon$ -greedy.

affects strategies such as  $\epsilon$ -greedy, that uniformly explore. This is further evidenced by the improvements seen in the *Softmax* and *Rank-based* ALS strategies—both of which *proportionally* explore, rather than uniformly.

#### Summary

In this section, six attribute-level strategies were studied via bilateral simulations across a variety of representative environmental contexts. Overall, results from some 7,500 simulations were reported. The main results of this significant empirical evaluation are:

- Based upon all the empirical data, Hypothesis 5.1 is accepted. While two strategies— $\epsilon$ -greedy and  $\epsilon$ -decreasing—performed the best, both were sensitive to certain environmental contexts, and neither dominated.
- Hypothesis 5.2, however, is rejected. Even though the environmental contexts were static, interactions between traders and marketplaces led to emergent dynamics, which favoured  $\epsilon$ -greedy in many cases, thus  $\epsilon$ -decreasing did not dominate as hypothesised.

- In general, strategies that depend on *absolute* reward values, e.g., *Softmax*, can be sensitive to a large number of environmental contexts because the absolute levels of rewards change between environments.
- The only difference between *EA* and *1+1 ES* is the size of the population. *1+1 ES* generally outperformed *EA*, suggesting the advantages of a larger population might be outweighed by the increased costs of evaluating it, in the environmental contexts considered.
- Charging contexts have a significant impact on the performance of ALS strategies, and not all strategies perform better in certain charging contexts.
- When the environment contains traders with constraints, there is a clear advantage, in some cases, to using ALS strategies that *proportionally*—rather than *uniformly*—explore the attribute-level space.

Thus, in terms of answering the overarching research question, the performance of attribute-level selection strategies can be significantly affected by many factors, including competing strategies, and the charging and trader contexts comprising the environment. Further, while  $\epsilon$ -greedy's performance is in general quite robust to environmental changes, no ALS strategy can be said to dominate all others, and thus generalise perfectly across all environmental contexts.

## 5.5 Market Niching in Multi-niche Environments

In this section, bilateral simulations using the *constraint-induced niches* and *preference-induced niches* trader contexts are considered. Because these trader contexts contain *multiple market niches*, outcomes involving the occupation of each market niche by a market-exchange, are possible. However, while results in previous section shed light on the ability of ALS strategies to compete over a *single* niche, typical outcomes in environments containing multiple market niches are unclear. As such, the overarching research question that this section takes a step towards answering is:

*What impact do different environmental contexts have on the abilities of competing candidate attribute-level strategies to find market niches in multi-niche environments?*

## 5.5. MARKET NICHING IN MULTI-NICHE ENVIRONMENTS

To make progress on this question, further simulation studies are carried out, across all of the previously considered charging contexts and multi-niche trader contexts, so that the following questions can be specifically answered:

- Which of the charging contexts facilitate the most efficient resource allocations, and thus provide the best means for locating market niches within these multi-niche trader contexts?
- What impact does the presence of each of the ALS strategies have on resource allocations within the system?
- What impact does the trader context, and thus preferences and constraints, have on the market niching process?

### Experimental setup

An experimental methodology, similar to that in Section 5.4.1 is carried out throughout this section, but with some differences. Firstly, simulated environmental contexts include either the *constraint-induced niches* or *preference-induced niches*, trader contexts. Secondly, rather than measuring market-exchange profit, these results focus on the efficiency of the resource allocations over the entire system, by using the *allocative efficiency* metric for multi-attribute resource allocations, defined in Section 4.5, on Page 111.

The higher the allocative efficiency in the system, the larger the total utility of all agents. The allocative efficiency of a perfectly *efficient* resource allocation is 1; however because traders always have an element of exploration in their market-selection, completely efficient allocations are realistically unattainable. While meaningful comparisons between efficiency of competing market-exchanges using different ALS strategies can be made, the numbers on their own say little about the actual *niching* behaviour of the exchanges. Therefore, throughout this section, visualisations of daily selected attribute-levels are provided, in the form of *heat maps*. Finally, *self-play* simulations are considered within these results, because how a strategy interacts with itself does affect the global efficiency of the system.

### 5.5.1 ‘Constraint-induced niches’ environments

This set of experiments considers environmental contexts involving the *constraint-induced niches* trader context. Recall that while traders within this context have no preferences over attributes, two separate populations of buyers exist, each with different minimum and maximum constraints. This leads to an environment where there are two market niches in these simulations, when the resource types  $\pi = \langle 0.6, 0.6 \rangle$  and  $\pi = \langle 1.0, 1.0 \rangle$  are specified. This environment presents considerable challenges to ALS strategies. For example, because many buyers and sellers are restricted in the types of resource they can trade, ALS strategies that move between desirable and undesirable points in the space are likely to repel many traders.

#### System-wide allocative efficiency

Table 5.8 highlights the *impact* that each of the attribute-level selection strategies have on the allocative efficiency of the system, when they are present within a simulation. Values in rows 3–8 represent the system-wide mean daily allocative efficiency for all simulations involving that strategy. For example, values in row three are arrived at by taking mean system-wide allocative efficiency measures of the simulations where  $\varepsilon$ -decreasing competed against:  $\varepsilon$ -greedy; EA; 1+1 ES; Rank-Based; Softmax; and itself. In line with the previous ALS strategy performance results,  $\varepsilon$ -decreasing and  $\varepsilon$ -greedy perform equally well. A *T-Test* of equality of means fails to reject the null hypothesis that the means are identical at significance level  $\alpha = 0.005$ ; this is not surprising given previous results. Secondly, when  $\varepsilon$ -greedy or  $\varepsilon$ -decreasing are involved in simulations, allocations are on average significantly more efficient, those that don’t include them. Statistical tests, against the third best strategy support this for each charging context. In the *bid/ask spread commission* context, a *Wilcoxon Signed-Rank test* comparing the  $\varepsilon$ -greedy Rank-based strategies reports a *p-value* of  $< 0.005$  and a

## 5.5. MARKET NICHING IN MULTI-NICHE ENVIRONMENTS

Strategy	Allocative Efficiency		
	Bid/Ask Spread charging context	Registration Fee charging context	Transaction Price Fee charging context
$\epsilon$ -decreasing	$0.602 \pm 0.081$	$0.566 \pm 0.109$	<b><math>0.716 \pm 0.068</math></b>
$\epsilon$ -greedy	$0.626 \pm 0.089$	$0.556 \pm 0.123$	<b><math>0.704 \pm 0.080</math></b>
EA	$0.395 \pm 0.133$	$0.365 \pm 0.114$	<b><math>0.490 \pm 0.119</math></b>
1+1 ES	$0.439 \pm 0.134$	$0.429 \pm 0.112$	<b><math>0.591 \pm 0.148</math></b>
Rank	$0.553 \pm 0.113$	$0.502 \pm 0.098$	<b><math>0.591 \pm 0.092</math></b>
Softmax	$0.367 \pm 0.152$	$0.305 \pm 0.122$	<b><math>0.695 \pm 0.114</math></b>
Mean (all)	$0.497 \pm 0.163$	$0.452 \pm 0.157$	<b><math>0.627 \pm 0.140</math></b>

Table 5.8: For each strategy, each data point provides the measure of system-wide mean daily allocative efficiency, over *all* simulations involving each strategy and its competitors. Thus, it captures the impact that the presence of that strategy typically has on resource allocations within the system. Results are separated into the three different charging contexts, thus each value is the mean from a sample of data points with size: 6 competitor variations  $\times$  50 simulation repetitions. A value of 1.0 would indicate a 100% efficient allocation for every day of every reported simulation. Emboldened values indicate highest reported efficiency across the three charging contexts, involving the strategy within that row. Emphasised values indicate the highest reported efficiency for any strategy involved within that single context.

*signed rank* of 8,368; the same test within the *registration fee* context reports a *p-value* of  $< 0.005$  and a *signed rank* of 11,850; and in the *transaction price fee* context,  $\epsilon$ -greedy versus *Softmax* resulted in no significant difference between the samples at a significance level  $\alpha = 0.005$ . Finally, in *all* cases, resource allocations are improved when the *transaction price fee* charging context is in use. Even though a higher fee is charged for executing a trade on resource  $\pi = \langle 1.0, 1.0 \rangle$  than,  $\pi = \langle 0.6, 0.6 \rangle$ , with this charging context, the overall profit from selecting niche  $\pi = \langle 0.6, 0.6 \rangle$  is clearly greater than sharing the profits at niche  $\pi = \langle 1.0, 1.0 \rangle$ .

### Market-exchange niching

While the reported efficiency values in Table 5.8 provide clues as to which of the ALS strategies lead to the most efficient allocations in different charging contexts, it is unclear exactly what these numbers mean in terms of actual *niching*



*behaviour*. To better understand ALS strategies' niching behaviour, visualisations are provided using data extracted from some of the simulations reported in Table 5.8. Within the simulated *constraint-induced niches* trader context there

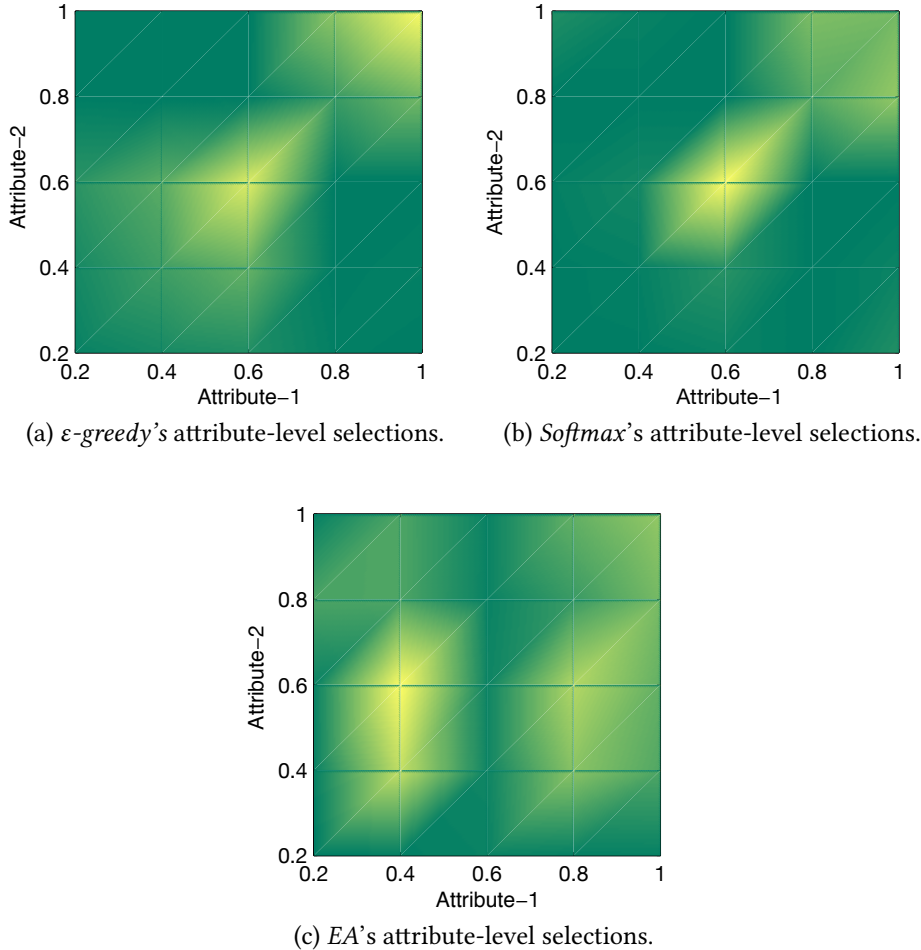


Figure 5.10: Heat maps showing the niching ability of various strategies for simulations involving the *transaction price fee* charging and *constraint-induced niches* trader, contexts. Each location on the  $x$  and  $y$  axes is a point in attribute-level space, and thus a resource type. Each daily attribute-level selection is plotted over *all* simulations involving the respective strategy. Thus, the visualisations provide a general overview of the strategy's niching behaviour. Lighter areas chose the associated attribute-levels more often. For bandit strategies, choices were always in the discrete set of points  $\{0.2, 0.4, 0.6, 0.8, 1.0\}$ , however, using interpolation techniques these reduced choices are mapped onto the real-space so that they can be compared to the real-value strategy, i.e., Figure 5.10c. The resource types indicating the market niches that satisfy the market segments are  $\pi = \langle 0.6, 0.6 \rangle$  and  $\pi = \langle 1.0, 1.0 \rangle$ .

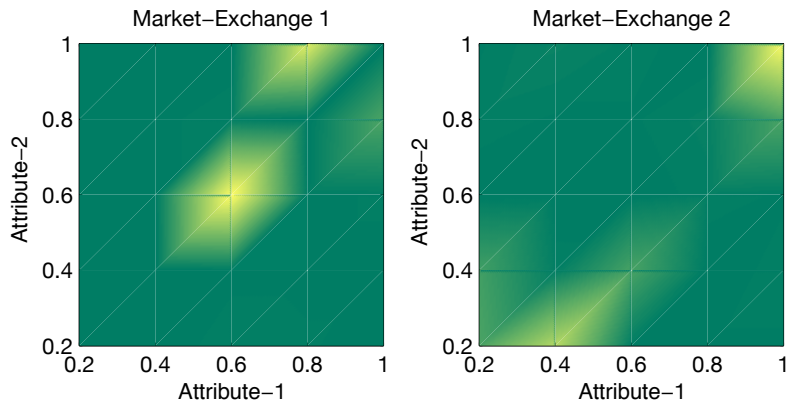
exist two market niches, at the points  $\langle 0.6, 0.6 \rangle$  and  $\langle 1.0, 1.0 \rangle$  in the attribute-level

## 5.5. MARKET NICHING IN MULTI-NICHE ENVIRONMENTS

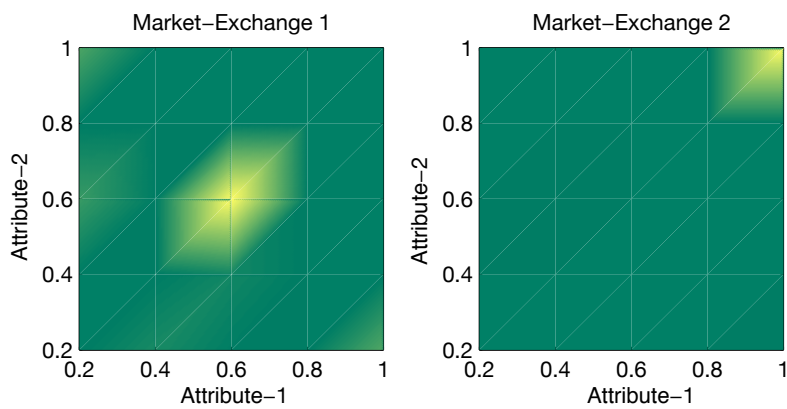
space. To get a better understanding of the general niching behaviour of some of the ALS strategies, *heat maps* were created, which allow attribute-level selection choices to be visualised easily. A heat map is created by plotting a 2D visualisation of attribute-level space, and colouring each point in the space according to the frequency it was chosen by an ALS strategy. For example, each heat map in Figure 5.10 shows *all*—some 1.5 million data points—daily attribute-level selections for each of the ALS strategies in its caption, across simulations against all competing strategies in the *transaction price fee* charging context.

In general,  $\epsilon$ -greedy (Figure 5.10a) and *Softmax* (Figure 5.10b) are able to locate both the niches successfully, regardless of the competing strategies in the environment. Note, *Softmax* has a better *concentration* or *focus* on the two niches than  $\epsilon$ -greedy, because it selects attribute-levels proportional to its rewards. Further, note that *Softmax* spends more time satisfying the market niche for resource  $\pi = \langle 0.6, 0.6 \rangle$ , rather than  $\pi = \langle 1.0, 1.0 \rangle$ ; this is because, despite rewards being based on transaction prices (which would be higher at  $\pi = \langle 1.0, 1.0 \rangle$ ), more traders can trade  $\pi = \langle 0.6, 0.6 \rangle$  because no sellers have minimum constraints, thus the volume of transactions increases the profitability for the exchange.

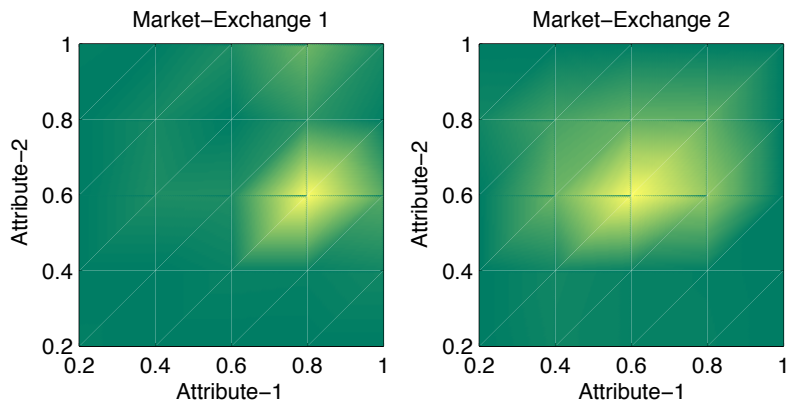
The *EA* strategy (Figure 5.10c) does not perform well in this trader context. While it regularly finds areas close to the niche  $\pi = \langle 1.0, 1.0 \rangle$ , it rarely finds the niche at  $\pi = \langle 1.0, 1.0 \rangle$ . Recalling Figure 5.3 on Page 5.3, it is possible that the *EA* strategy has trouble finding the smaller niche. Figure 5.11 shows the typical niching behaviour for some ALS strategies in individual simulations. By running *self-play* simulations, where both exchanges use the same ALS strategy, it becomes possible to see if the behaviour of the strategies in Figure 5.10 is due to their own strategy, or the presence of others. For example, *Softmax* is exceptionally well suited to this environment. Because it explores *proportionally*, i.e., based on reward values, each exchange sticks to its own niche, resulting in a stable outcome, and the highest allocative efficiency. When exchanges both use  $\epsilon$ -greedy, however, they *encroach* on each other's niche, due to uniformly random



(a) Typical niching behaviour of two market-exchanges using  $\epsilon$ -greedy strategies; mean allocative efficiency—76%.



(b) Typical niching behaviour of two market-exchanges using *Softmax* strategies; mean allocative efficiency—78%.



(c) Typical niching behaviour of two market-exchanges using *EA* strategies; mean allocative efficiency—31%.

Figure 5.11: Typical niching behaviour of several attribute-level strategies when in competition with themselves, during single simulations using the *transaction price fee* charging and *constraint-induced niches* trader, contexts. Two niches exist:  $\pi = \langle 0.6, 0.6 \rangle$  and  $\pi = \langle 1.0, 1.0 \rangle$ . *Softmax* (b) works well in *self-play* because each *Softmax* strategy sticks to its niche, while  $\epsilon$ -greedy (a) strategies encroach on each other; neither *EA* strategies (c) locate the second niche. See Figure 5.10 for help reading the *heat maps*.

## 5.5. MARKET NICHING IN MULTI-NICHE ENVIRONMENTS

exploration; inevitably both niches won't be satisfied at all times. Finally, as Figure 5.11c highlights, neither exchange using the *EA* strategy is able to locate the  $\pi = \langle 1.0, 1.0 \rangle$  niche. This is possibly because neither strategy is able to generate mutations that take it to the smaller second peak and thus both are trapped in competition over a single niche, resulting in half of the buyers being unable to trade at all.

### 5.5.2 'Preference-induced niches' environments

Finally, the *preference-induced niches* environment is considered. Again, there are two market niches, but due to trader preferences, these are located at points corresponding to resource types  $\pi = \langle 0.2, 1.0 \rangle$  and  $\pi = \langle 1.0, 0.2 \rangle$ . A further difference in this trader context is that there are no *infeasible* parts of the attribute-level space; all traders can potentially trade *any* resource type.

#### System-wide allocative efficiency

Based upon Table 5.9, the *preference-induced niches* trader context increases the difficulty in finding market niches, resulting in overall less efficient allocations compared to the *constraint-induced niches* context (Table 5.8). While relative performance between strategies is similar to the *constraint-induced niches* trader context, all allocation efficiencies are generally lower, indicating preferences significantly affect all the strategies' niching ability. Of particular interest is the observation that the most efficient allocations no longer arise when exchanges charge according to the *transaction price fee* charging context. Rather, the *bid/ask spread commission* charging context provides a better indication of market niches, though not with statistical significance. However, it suggests the *transaction price fee* charging context does not correlate well with the positions of preference-induced niches.

Strategy	Allocative Efficiency		
	Bid/Ask Spread charging context	Registration Fee charging context	Transaction Price Fee charging context
$\epsilon$ -decreasing	<b><math>0.566 \pm 0.107</math></b>	$0.420 \pm 0.054$	$0.495 \pm 0.033$
$\epsilon$ -greedy	<b><math>0.564 \pm 0.090</math></b>	$0.421 \pm 0.061$	$0.507 \pm 0.039$
EA	<b><math>0.403 \pm 0.087</math></b>	$0.318 \pm 0.053$	$0.399 \pm 0.046$
1+1 ES	$0.473 \pm 0.087$	$0.351 \pm 0.046$	<b><math>0.476 \pm 0.046</math></b>
Rank	<b><math>0.498 \pm 0.042</math></b>	$0.371 \pm 0.055$	$0.433 \pm 0.046$
Softmax	$0.375 \pm 0.079$	$0.306 \pm 0.033$	<b><math>0.480 \pm 0.058</math></b>
Mean (all)	<b><math>0.480 \pm 0.118</math></b>	$0.365 \pm 0.070$	$0.463 \pm 0.060$

Table 5.9: For each strategy, each data point provides the measure of system-wide mean daily allocative efficiency, over *all* simulations involving each strategy and its competitors. Results are separated into the three different charging contexts, thus each value is the mean from a sample of data points with size: 6 competitor variations  $\times$  50 simulation repetitions. All simulations used the *preference-induced niches* trader context. A value of 1.0 would indicate a 100% efficient allocation for every day of every reported simulation. Emboldened values indicate highest reported efficiency across the three charging contexts, involving the strategy within that row. Emphasised values indicate the highest reported efficiency for any strategy involved within a single charging context.

### Market-exchange niching

Using the *bid/ask spread commission* charging context, general attribute-level selection performance of three of the ALS strategies is provided in Figure 5.12. Unlike similar visualisations with the *constraint-induced niches* trader context in place (Figure 5.10), *Softmax* appears to struggle to locate the niches, further evidence for its sensitivity to the charging context. The *EA* strategy seems unable to locate *either* of the niches, and aggregated over the many simulation runs, it has no tendency to focus on any particular point in attribute-level space. Because *1+1 ES* works in the same way, but without a population, it could be argued that the cost of evaluating a—likely poor—population, drives away traders to the other exchange, so no matter where *EA* moves to its profit does not improve, which would explain the generally uniform coverage of the attribute-level space in Figure 5.12c.

Finally, in Figure 5.13 typical market-niching behaviours in *self-play* simulations are examined, to better understand how well typical strategies locate

## 5.5. MARKET NICHING IN MULTI-NICHE ENVIRONMENTS

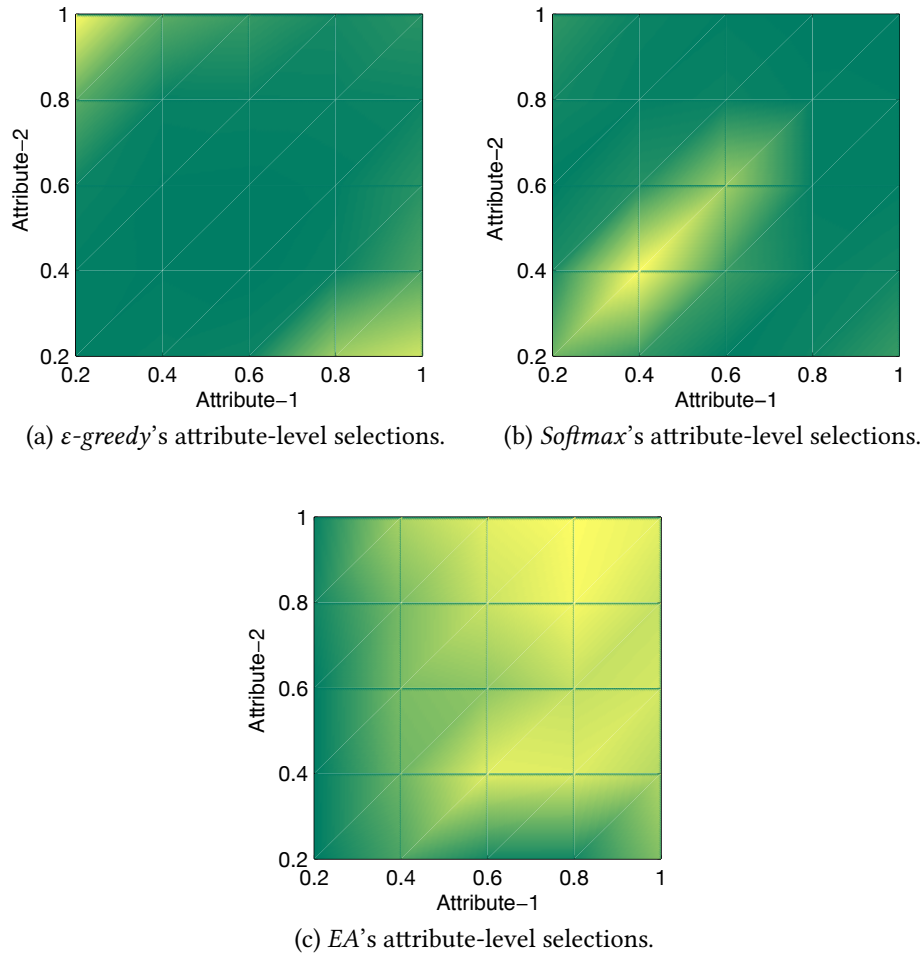


Figure 5.12: Heat maps showing the niching ability of various strategies for simulations involving the *bid/ask spread commission* charging and *preference-induced niches* trader, contexts. Each location on the  $x$  and  $y$  axes is a point in attribute-level space, and thus a resource type. Each daily attribute-level selection is plotted over *all* simulations involving the respective strategy. Thus, the visualisations provide a general overview of the strategy's niching behaviour. Lighter areas correspond to more frequently chosen attribute-levels. The resource types indicating the market niches that satisfy the market segments are  $\pi = \langle 0.2, 1.0 \rangle$  and  $\pi = \langle 1.0, 0.2 \rangle$ .  $\epsilon$ -greedy is able to locate either of the market niches in simulations it takes part in. *Softmax*, already shown to be sensitive to the *bid/ask spread commission* charging context, is unable to locate the market niches, and is perhaps attracted to a very unusual part of the space because bid/ask spreads, and thus its profits, can increase in very inefficient markets, such as ones around  $\pi = \langle 0.2, 0.2 \rangle$ . *EA* has no general tendency to regularly focus on any point in the space suggesting that its profits are typically flat for all points, which may in part be due to driving traders away during the evaluation of its solution population.

market niches in the *preference-induced niches* trader context, and thus the impact

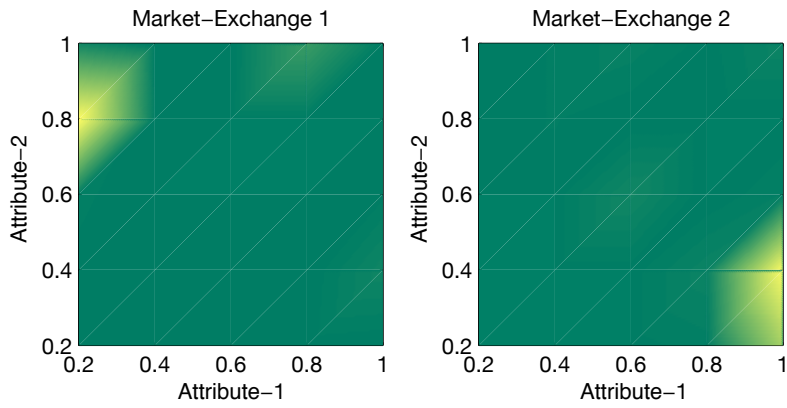
that preferences and constraints have upon the market niching problem. Based upon these individual simulations, it is clear that the *preference-induced niches* trader context significantly worsens the niching ability of the ALS strategies; in all cases allocative efficiency was worse than the equivalent simulations in Figure 5.11. At this point, it is important to remember that the exchanges are attempting to *maximise profit*, and not social welfare (which is a desired emergent behaviour). Recall that the *bid/ask spread commission* charging context specifies exchanges charge the difference between traders' bid and ask offers, which in a competitive market equilibrium would be zero. When market niches are satisfied, competitive market equilibrium can be more closely approached, which reduces, in this charging context, market-exchange profits. Thus, as seen by the  $\epsilon$ -greedy results (Figure 5.13a), some ALS strategies are focussing on points in the space that purposely lead to *less* inefficient allocations than could otherwise be achieved, in order to boost profits.

### 5.5.3 Summary

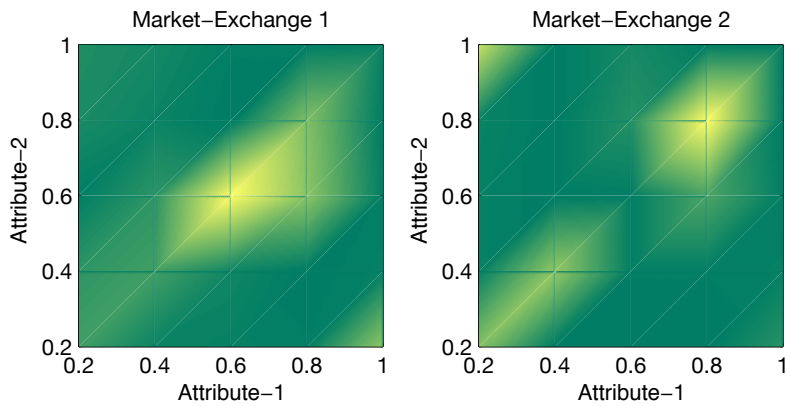
In terms of the overarching research question for this section, within multi-niche environments, several factors affect ALS strategies' abilities to find market niches. Based upon the simulation results in this section:

- No single charging context facilitates the most efficient resource allocations. While the *transaction price fee* charging context helps locate niches in the *constraint-induces niches* trader context, in the *preference-induced niches* the most ideal charging context (*bid/ask spread commission*) rewards exchanges to maintain a slightly inefficient market (Figure 5.13a), indicating further work is needed in this area;
- The presence of the  $\epsilon$ -greedy,  $\epsilon$ -decreasing, and in some cases, *Softmax* strategies in the environment tend to improve the efficiency of allocations, indicating their success in tackling the automatic market niching problem;
- The *EA* strategy significantly under-performed, likely due to premature convergence, indicating diversity mechanisms such as *fitness-sharing schemes* [149] may improve the evolutionary optimisation approach to the market niching problem;

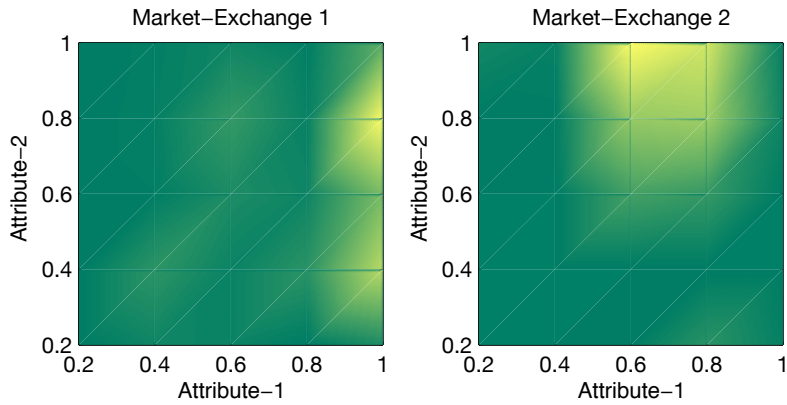
5.5. MARKET NICHING IN MULTI-NICHE ENVIRONMENTS



(a) Typical niching behaviour of two market-exchanges using  $\epsilon$ -greedy strategies; mean allocative efficiency—64%



(b) Typical niching behaviour of two market-exchanges using *Softmax* strategies; mean allocative efficiency—36%



(c) Typical niching behaviour of two market-exchanges using *EA* strategies; mean allocative efficiency—39%

Figure 5.13: Typical niching behaviour of several attribute-level strategies when in competition with themselves, during single simulations using the *bid/ask spread commission* charging and *preference-induced niches* trader, contexts. Two niches exist:  $\pi = \langle 0.2, 1.0 \rangle$  and  $\pi = \langle 1.0, 0.2 \rangle$ . Unlike similar visualisations for simulations involving the *constraint-induced niches* trader and *transaction price fee* trader, contexts (Figure 5.11), all three strategies seem unable to locate market niches to the same accuracy, because the charging context rewards market inefficiency. See Figure 5.10 for help reading the *heat maps*.



- Preferences have a *significant* impact on the ability of ALS strategies to find niches.

## 5.6 Conclusions and Discussion

This chapter introduced the newly formulated *automatic niching problem*. The automatic niching problem describes the challenge that a market-exchange agent faces when specifying which resource type should be traded within its market. This problem is particularly challenging because the environment is complex, dynamic, and *coevolving*. Two approaches were considered for tackling the resulting reinforcement learning problem: an *n-armed bandit* approach and an *evolutionary optimisation* approach. Based upon these approaches, the performance of several candidate *attribute-level selection* (ALS) strategies was empirically assessed, in representative environmental contexts.

Results from this chapter showed that all candidate strategies are sensitive to at least some environmental factors, and thus none can be seen to *generalise* across all contexts, but in most environmental contexts, at least one of the strategies performs very well, identifying the market niches in the environment. Cai et al. [23] find that in single-attribute market environments, traders within the same cohort migrate to similar markets, which improves efficiency. Results within this chapter show, for a more complex multi-attribute resource allocation domain, that not only do traders within the same cohort migrate to similar markets, but competing market-exchanges, using ALS strategies, are able to automatically find market niches, and in some cases self-organise to satisfy all environmental niches, leading to the desirable allocations of complex resources. The main contributions of this chapter are:

- The first clear formulation of the automatic market niching problem;
- The proposal of two general approaches to tackle the automatic market niching problem;

## 5.6. CONCLUSIONS AND DISCUSSION

- A comprehensive computational study of the two approaches, instantiated as six attribute-level selection strategies, in representative environments that market exchanges might expect to find themselves in;
- Rigorous statistical analysis, discussion, and visualisation of the impact that the representative environmental contexts have on the performance of the attribute-level selection strategies. Particularly:
  - how environmental contexts affect the profitability of attribute-level selection strategies;
  - how environmental contexts affect the niching ability of competing attribute-level selection strategies in multi-niche environments.

Although this chapter has not fully answered the question of which is the best attribute-level selection strategy *in general*, it has made a significant step towards understanding how the performance of different attribute-level selection strategies are impacted by various environmental factors, which has facilitated a clear study of the suitability of two reinforcement learning approaches to this newly formulated problem.

Within the environmental contexts considered, the  $\epsilon$ -greedy and  $\epsilon$ -decreasing n-armed bandit ALS strategies performed the strongest of the candidates, but the *proportional* nature of *Softmax*'s strategy exhibited extremely promising behaviour when the environmental context *suites* its parametric setting. Future work will look at how useful features of these strategies can inspire novel strategies that perform better, and aren't sensitive to parameter settings. Out of the two approaches considered, the evolutionary optimisation approach did not seem to perform as well. Being restricted to exploring neighbourhood search space appears to be a disadvantage for the automatic market niching problem. In many cases it appeared that the expense of having to evaluate a population of solutions drove traders away, and even if useful solutions were evaluated, the fitness landscape had been shifted by traders

selecting competing marketplaces. However, the ability for evolutionary approaches to explore *any* part of the search space is certainly advantageous in *general*, e.g, when niches aren't well-defined, or don't exist in points that are represented in an ALS strategy's action set. Thus, future work will consider how the performance of evolutionary algorithms can be improved, perhaps using *fitness-sharing schemes* [149] to more efficiently explore the space.

**CHAPTER 6**

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**IMPROVED RESOURCE  
ALLOCATIONS USING SUBJECTIVE  
REPUTATIONS**

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Within this thesis, trading agents have been assumed to use only private information, in the form of historical trading profits, to form the basis of their market-selection decisions. Further, it has been assumed that traders have been present for the entire duration of simulations, and thus have been able to learn appropriate market-selection signals over time, in order to identify the most profitable markets to join. However, in real-world open marketplaces, traders—and on longer time scales, market-exchanges—join and leave the system at different times. Further, the recent empirical analysis of *attribute-level selection strategies* in Chapter 5 has shown that over time autonomous market-exchanges' behaviour can change, in terms of the market-niche that they satisfy, and how attractive they are to traders, which may change traders' preferences over them as time progresses.

This chapter considers, for the first time, the application of a reputation approach to the problem of facilitating market-selection in the domain of multi-attribute resource allocation via competing marketplaces. The chapter demonstrates via simulation studies that reputation-based market-selection strategies can lead to more efficient resource allocations in a variety of dynamic environments, and provides evidence to suggest that a *subjective* reputation approach is very important for facilitating efficient allocations in multi-attribute resource allocation systems. Specifically, the main contributions of this chapter are: (i) the first application of a reputation approach to the problem of market-selection in a multi-attribute market-based system containing competing marketplaces; (ii) consideration of both strategic and non-strategic reputation manipulation models, and the proposal of a novel trader behaviour model for strategically manipulating supply and demand, in a bid to subvert marketplace reputations; (iii) to demonstrate, via simulation studies, the applicability of both objective and subjective reputation approaches to facilitating better market-selection decisions over competing marketplaces, in a variety of dynamic and uncertain environmental settings. The rest of this chapter is organised as

## 6.1. MOTIVATION

follows. First, in Section 6.1, the proposal of applying a reputation approach to the problem of market-selection is further discussed, and specific research questions formulated. In Section 6.2, a Bayesian statistics approach, which has been found to be successful at predicting agent behaviour in other e-market applications is formally introduced, and it is demonstrated how this approach can be integrated into the market-based approach introduced in this thesis. A Bayesian approach to reputation formation relies on accurate evidential information, in the form of accurate reports from agents. Section 6.3 considers different forms of information manipulation and proposes two behaviour models, which could affect traders' reputation-based market-selection decisions. Section 6.4 demonstrates how a Bayesian reputation approach can be made subjective by learning how information from different sources should be weighted. Finally, in Section 6.5 a thorough empirical analysis is undertaken to test several hypotheses involving the ability of both objective and subjective reputation approaches to facilitate trader market-selection in a variety of dynamic environments. The chapter is concluded in Section 6.6.

## 6.1 Motivation

One of the themes within this thesis is that of *generalisation* and *robustness* of mechanisms within complex, adaptive market-based systems. The previous chapter analysed mechanisms for automatically identifying and satisfying market niches, in an effort to improve market-exchanges ability to generalise over different trader contexts. In the same spirit, the motivation for the work in this chapter is to improve traders' market-selection decisions when trading in dynamic and uncertain market environments, which also takes a step towards the design of more robust resource allocation systems in general. On a specific level pertaining to the market-based system studied in this thesis, the work in this chapter is motivated by the following observations: (*i*) so far, the same traders

have been assumed to exist within the system at all times, while in real-world open marketplaces traders—and on longer time scales, market-exchanges—join and leave the system at different times; (ii) recent empirical analysis of *attribute-level selection strategies* in Chapter 5 has shown that over time, autonomous market-exchanges' behaviour can change, both in terms of their market-niching, and how attractive they are to traders; and (iii) traders have to learn over time, using only private historical profit information, based upon direct interactions with market-exchanges, which market is best to join.

These observations lead to questions about the expense traders incur learning these *market-selection signals*, in terms of the *time* taken exploring possible markets, and ultimately the *cost* in terms of profits sacrificed from potentially sub-optimal decisions taken during the learning process. While for a single *static* population of traders, the eventual benefits of learning accurate market-selection signals will outweigh the initial costs after sufficient time in the environment, for a population under *churn* this may not be the case, if for example agents leave the system before they have recovered the costs of learning the signals. In terms of the overall impact on the system, which is always of interest from a designer's point of view, these dynamics can significantly hinder efficiency of resource allocations in the system. Accurate market-selection signals are particularly important if traders have preferences and constraints over multi-attribute resources, and these are allocated via autonomous competing marketplaces, because system efficiency is maximised when cohorts of traders within the same *market segment* trade within the market occupying that market niche.

As discussed in Chapter 2, *reputation* can act in a signalling role [141, 87], providing publicly generated signals describing the expected behaviour of other agents. Because reputations are leveraged from the aggregated direct experiences of agents, they can be used by an agent to predict behaviour of another it has not yet directly interacted with. And while private, direct observations are likely to

## 6.1. MOTIVATION

be more accurate, agents joining a system may benefit more from less accurate publicly generated signals than private ones that are expensive to learn. A small amount of previous work has looked at the issue of trust and reputation within continuous double-auction settings, concentrating on how the average quality of resources sold by sellers can be signalled to buyers within the market [98, 170]. However, it uses objective measures for trust and reputation and does not consider strategic reporting of agents. Probabilistic reputation approaches have been proposed and developed to support agent decision-making using sound statistical methods [80]. Further, these foundations have been built upon to enable agents to deal with false reporting or malicious behaviour, of the type expected in open electronic communities [166, 165, 97]. However, these *subjective* Bayesian approaches have not been applied within the context of dynamic market-based environments where agents' preferences and rational behaviour can differ, or for measuring the reputation of market-exchanges running multi-attribute resource markets, whose behaviour cannot be described as simply 'good' or 'bad'. Further, the entry and exit dynamics (trader churn) of a market-based system directly influence the outcomes of agent interactions, and thus potentially this reputation approaches' success in these environments.

### 6.1.1 Research questions

The focus of this chapter is the applicability of subjective Bayesian reputation approaches to the multi-attribute resource allocation model introduced in Chapter 4. Particular focus is given to removing the assumption that traders exist within the system for the duration of simulations, and instead it is assumed the system possesses a constant *trader churn*, where traders enter and exit the system at different times. The main research questions considered in this chapter are:

- *What impact do trader churn dynamics have on traders' profitability, and the efficiency of resource allocations, when traders do or don't, use reputation to make market-selection decisions?*



- How well do objective and subjective reputation approaches deal with the presence of strategic and non-strategic reputation information manipulation?
- How well do objective and subjective reputation approaches provide market-selection signals to different market segments in multi-niche environments?
- What properties do emergent recommender networks possess?

## 6.2 A Bayesian Reputation Approach

In this section, a reputation approach, grounded in Bayesian statistics, and based upon the use of Beta distributions is described. The *Beta distribution* is a continuous probability distribution that can be used to represent probability distributions of binary events [80]. The beta distribution is defined in general by two *shape* parameters:  $\alpha$  and  $\beta$  [38]. The beta distribution is use extensively in Bayesian statistics for estimating the posterior probability of binary events [25], making it useful for applications that involve positive and negative experiences. The probability density function for the beta distribution is defined as:

$$f(p|\alpha, \beta) = \frac{p^{\alpha-1}(1-p)^{\beta-1}}{\int_0^1 u^{\alpha-1}(1-u)^{\beta-1} du}, \text{ where } 0 \leq p \leq 1, \alpha, \beta > 0 \quad (6.1)$$

The expected value of the beta distribution is simple to calculate:

$$E(p) = \frac{\alpha}{\alpha + \beta}. \quad (6.2)$$

Supposing a process has two possible outcomes: positive ( $h$ ) and negative ( $s$ ), then a Beta distribution can be used to estimate the probability of observing a positive outcome based on a history of observations. Assuming  $\hat{h}$  and  $\hat{s}$  are the frequency of observed positive and negative outcome, the distribution for estimating the probability of observing a positive outcome  $h$  has parameters  $\alpha = \hat{h} + 1$  and  $\beta = \hat{s} + 1$  (ensuring  $\alpha, \beta > 0$  in the absence of observations). The *prior distribution*  $f(p|1, 1)$  (where  $\alpha = 1, \beta = 1$ ), is special, as it is also the standard *Uniform*

## 6.2. A BAYESIAN REPUTATION APPROACH

*Distribution.* It can model the absence of knowledge about a process. As such, all possible values of  $p$  are equally likely to be observed; the *prior probability* of observing a positive event in a process is therefore  $E(p) = 0.5$ . More process observations increase the confidence that the posterior probability  $f(p|\alpha, \beta)$  of observing a positive outcome of a process represents the *true* probability of observing a positive outcome. Because the Beta distribution is a continuous probability distribution— $p$  has infinitely many values—it is not possible to assign a finite probability to observing a specific outcome, so one assigns a probability to a *range* of outcomes [175].

To estimate the confidence we have that the expected value of the beta distribution is the true probability of observing a positive outcome of a process, we can measure the integral of the distribution between two bounds defined by  $\varepsilon$ , commonly done with the *Beta Cumulative distribution function*:

$$F(p) = I_p(\alpha, \beta) = \frac{\int_0^p u^{\alpha-1}(1-u)^{\beta-1} du}{\int_0^1 u^{\alpha-1}(1-u)^{\beta-1} du}, \text{ where } 0 \leq x \leq 1; \alpha, \beta > 0 \quad (6.3)$$

In Equation 6.3,  $I_p(\alpha, \beta)$  is the regularised *Incomplete Beta Function*. Supposing some upper and lower bound defined by  $\varepsilon$ , confidence is estimated as follows:

$$\gamma_p = I_{p+\varepsilon}(\alpha, \beta) - I_{p-\varepsilon}(\alpha, \beta) \quad (6.4)$$

Intuitively, the more observations one can make, generally the more confident one can be about how close  $E(p)$  is to the true probability of observing a positive outcome to the process being modelled.

### 6.2.1 Representing trust with Beta distributions

Reputations are formed from the aggregations of many individual's direct opinions of others, which are typically described by *trust* values. The Beta

distribution forms the basis of market-exchange reputations system, by representing the *trust* a trader has in a market-exchange. Each trading-day, traders interacting with market-exchanges each observe three possible outcomes: (i) the trader successfully trades with another trader, resulting in the trader making a positive *profit*; (ii) the trader trades but makes zero profit, or the trader is unable to trade but does not otherwise incur a loss; or (iii) the cost of exchange charges are greater than any profit made from a possible trade, resulting in a net loss. The three possible outcomes a trader  $a_i$  could observe after a trading day  $t$  in  $m_k$ 's market, are represented by  $o_{a_i, m_k}^t$ :

$$o_{a_i, m_k}^t = \begin{cases} 1 & \text{if } P_{a_i}^t > 0 \\ 0.5 & \text{if } P_{a_i}^t = 0 \\ 0 & \text{if } P_{a_i}^t < 0, \end{cases} \quad (6.5)$$

where  $P_{a_i}^t$  is the daily profit made by  $a_i$  on day  $t$ . Though it may seem unlikely that a trader would trade and make exactly zero profit (case two in Equation 6.5), it is more likely that a trader might join an exchange that does not charge registration fees, but not manage to successfully trade. In such a case it seems unreasonable to assign the same outcome as that which a trader incurring a loss would experience (case three), thus case two neither labels the experience positively or negatively while still adding information to the model in the form of a neutral experience. While the outcomes traders can expect are ternary in this model, the shape parameters for a Beta distribution can still be updated each day in the same way as done in similar implementations for binary outcome models in other domains [80, 165, 97], because it is a continuous distribution. The Beta distribution is updated after an observation accordingly:

$$\begin{aligned} \alpha_{a_i, m_k}^{t+1} &= \alpha_{a_i, m_k}^t + o_{a_i, m_k}^t \\ \beta_{a_i, m_k}^{t+1} &= \beta_{a_i, m_k}^t + 1 - o_{a_i, m_k}^t \end{aligned} \quad (6.6)$$

## 6.2. A BAYESIAN REPUTATION APPROACH

The *interaction history* between  $a_i$  and  $m_k$  is represented by  $\alpha_{a_i, m_k}^t$  and  $\beta_{a_i, m_k}^t$ . When  $t = 0$ ,  $\alpha_{a_i, m_k}^t = \beta_{a_i, m_k}^t = 1$ , so that in the absence of any observations of interactions between  $a_i$  and  $m_k$ , the prior Beta distribution will be formed. Finally, *trust*  $\tau_{a_i, m_k}$  that a trader  $a_i$  has in market-exchange  $m_k$  can be defined:

$$\tau_{a_i, m_k}^t = E[p_{a_i, m_k} | \alpha_{a_i, m_k}^t, \beta_{a_i, m_k}^t] = \frac{\alpha_{a_i, m_k}^t}{\alpha_{a_i, m_k}^t + \beta_{a_i, m_k}^t} \quad (6.7)$$

As one can see from Equation 6.7,  $\tau_{a_i, m_k}^t$  is the expected value of the distribution describing the probability  $p_{a_i, m_k}$  that trader  $a_i$  will make a profitable trade when it next joins market-exchange  $m_k$  on trading day  $t + 1$ .

### Time discounting

The dynamics of any open multi-agent system mean that either behaviours or perception or behaviours can change over time. In accordance with previous Bayesian reputation approaches [81, 97], the Beta distribution used to form  $\tau_{a_i, m_k}$  is discounted at the end of every trading day  $t$ , by updating  $\alpha_{a_i, m_k}$  and  $\beta_{a_i, m_k}$  for each market-exchange  $m_k$ :

$$\begin{aligned} \alpha_{a_i, m_k}^t &= 1 + \alpha_{a_i, m_k}^t \times \delta^{\Delta t} \\ \beta_{a_i, m_k}^t &= 1 + \beta_{a_i, m_k}^t \times \delta^{\Delta t} \end{aligned} \quad (6.8)$$

where  $\delta \in [0, 1]$  represents the *aggressiveness* by which old information contributes to current trust values, and is thus forgotten. When  $\delta = 1.0$ , all historical outcomes  $o_{a_i, m_k}$  contribute equally to  $\alpha_{a_i, m_k}$  and  $\beta_{a_i, m_k}$ , while when  $\delta = 0.0$ , all previous outcomes are immediately forgotten and only the most recent interaction is considered in building the trust value. In all the simulations  $\Delta t = 0.95$ , which was found to be not too aggressive. Figure 6.1 shows that in the absence of new observations, a beta distribution (and thus trust) that  $a_i$  has for  $m_k$  decays back to the prior distribution; lowering the discounting factor increases the decaying process.

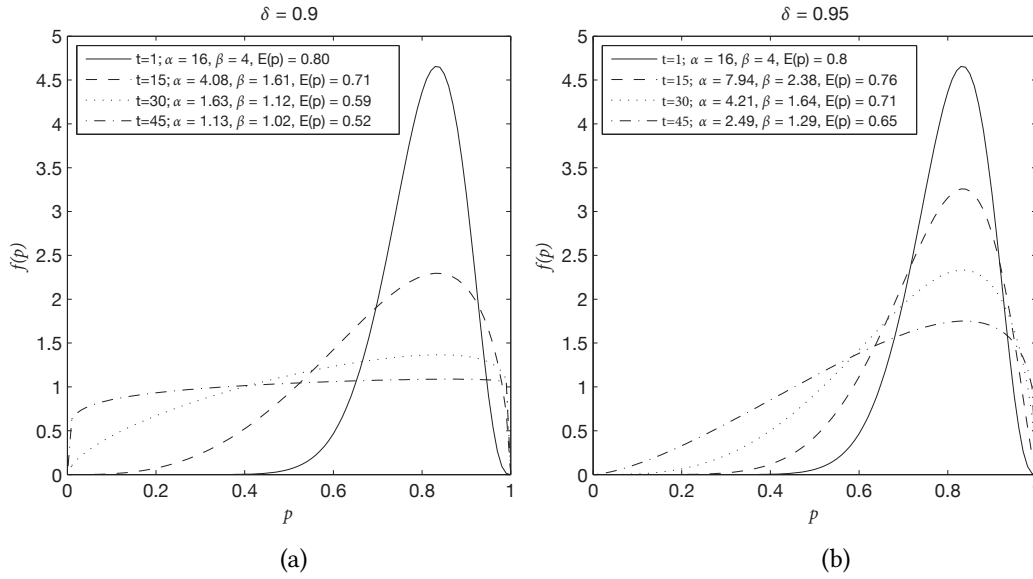


Figure 6.1: The effect of different time discounting factors on beta distributions representing interaction histories. A lower discount factor of  $\delta = 0.9$  in Figure 6.1a leads to more aggressive forgetting of older information over time  $t = 1 \dots 15 \dots 30 \dots 45$ , compared to a higher value of  $\delta = 0.95$  in Figure 6.1b. This example assumes no new observations are added each time step, thus the decaying process reduces each distribution towards the *uniform distribution*.

## 6.2.2 Combining opinions to form reputations

Now we have defined how traders can generate *trust* values for market-exchanges using beta distributions built from previous interactions, we can show how traders can combine others traders' trust values to form market-exchange *reputations*. Again, the Beta distribution has some nice properties for forming market-exchange reputations by combining the traders' trust distributions they hold for each market-exchange. Aggregating multiple separate Beta distributions is a matter of combining the shape parameters of the associated distributions [97], e.g.,  $f(p|\alpha_1, \beta_1) + f(p|\alpha_2, \beta_2) = f(p|\alpha_1 + \alpha_2, \beta_1 + \beta_2)$ . For this model, a trader  $a_i$  gathers other traders' interaction histories with market-exchange  $m_k$ , by asking

## 6.2. A BAYESIAN REPUTATION APPROACH

each trader  $a_j \in \mathcal{T}$  for their  $\alpha_{a_j, m_k}$  and  $\beta_{a_j, m_k}$  values as shown in Equation 6.9.

$$\alpha_{a_i, m_k}^{rep, t} = \sum_{j=1, j \neq i}^{|\mathcal{T}|} \alpha_{a_j, m_k}^t - 1 \quad (6.9)$$

$$\beta_{a_i, m_k}^{rep, t} = \sum_{j=1, j \neq i}^{|\mathcal{T}|} \beta_{a_j, m_k}^t - 1$$

By decreasing each  $\alpha_{a_i, m_k}^t$  and  $\beta_{a_i, m_k}^t$  by unity other agents' prior distributions are removed from the reputation calculation, as their uncertainty should not contribute.  $a_i$  can then use these values to build an aggregated beta distribution representing the combined opinions of other agents. Figure 6.2, shows visually

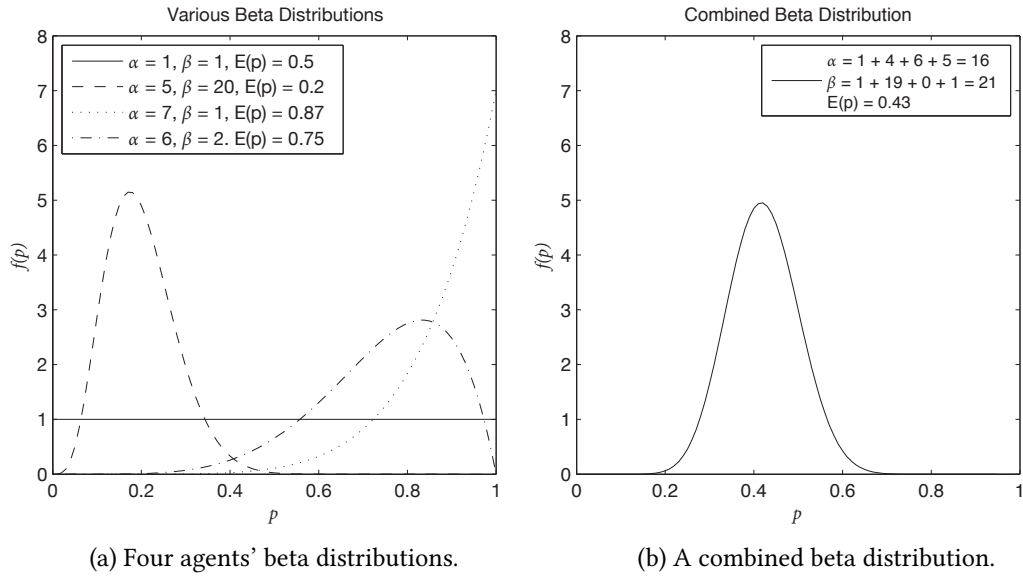


Figure 6.2: An example of how combining beta distributions is a matter of aggregating the  $\alpha$  and  $\beta$  parameters of the relevant distributions. Although two distributions in Figure 6.2a have high expected values, i.e., 0.75 and 0.87, the expected value of the combined distribution in Figure 6.2b is only 0.43, because a distribution with a low expected value of 0.2 in Figure 6.2a contains many observations, and impacts the combined distribution more.

how various beta distributions can be combined to form an aggregated beta distribution. In this case, it is assumed that a trader  $a_i$  has no direct information on market-exchange  $m_k$ , thus  $\alpha_{a_i, m_k} = \beta_{a_i, m_k} = 1$ ; this is the (prior) uniform

distribution shown in Figure 6.2a.  $a_i$  asks other traders for their interaction histories with  $m_k$ , and three of them provide  $\alpha$  and  $\beta$  values that form the remaining three distributions in Figure 6.2a. Trader  $a_i$  then combines these with its own prior distribution to form an overall distribution, which it can use to estimate the probability that joining market-exchange  $m_k$  will result in a profitable trade. In terms of this model's application of reputation, the value  $\rho_{a_i, m_k}^t$  is defined to represent the reputation of market-exchange  $m_k$  from the point of view of trader  $a_i$ :

$$\rho_{a_i, m_k}^t = \frac{\alpha_{a_i, m_k}^t + \alpha_{a_i, m_k}^{rep, t}}{\alpha_{a_i, m_k} + \alpha_{a_i, m_k}^{rep, t} + \beta_{a_i, m_k}^t + \beta_{a_i, m_k}^{rep, t}} \quad (6.10)$$

Equation 6.10 is the expected value of the distribution shown in Figure 6.2b; due to Equation 6.6,  $\rho_{a_i, m_k}^t$  includes the prior distribution when it combines the direct information that  $a_i$  has of  $m_k$  with information provided by others.

### 6.2.3 Making market-selection decisions using trust and reputation

Direct information is usually more accurate than indirect information obtained from third parties [18]. One approach to this—and one followed in this model—is to prefer to use trust when there is enough confidence in an assessment [166]. This is applied in this market-based model by specifying that traders prefer to use trust to make *market-selection decisions*. However, if a trader has not interacted enough with a market-exchange recently, then it will use publicly available information to form a reputation of the market-exchange. The decision of which information a trader  $a_i$  will use to create a market-selection signal  $\zeta_{a_i, a_j}^t$  at time  $t$ , concerning market-exchange  $m_k$ , is made as follows:

$$\zeta_{a_i, m_k}^t = \begin{cases} \tau_{a_i, m_k}^t & \text{if } \gamma_{a_i, m_k} \geq \gamma_{a_i}^* \\ \rho_{a_i, m_k}^t & \text{otherwise} \end{cases} \quad (6.11)$$

### 6.3. MODELLING UNCERTAIN MARKET-BASED ENVIRONMENTS

where  $\gamma_{a_i, m_k}$  is measured according to the Incomplete Beta Function from Equation 6.4;  $\gamma_{a_i}^*$  represents a *confidence threshold* that agent  $a_i$  uses to decide whether it needs to use reputation information to form a market-selection signal.

In previous work in this thesis, traders have been using the  $\varepsilon$ -greedy market-selection strategy defined in Section 4.4.3, on Page 108, which uses daily profit to learn the market-selection signals that govern market selection. As a basis for comparing the impact that reputation has on market-selection, compared to private profit information, the  $\varepsilon$ -greedy market-selection strategy is altered to incorporate reputation in the market-selection process in two ways: (i) the discounting portion of the  $\varepsilon$ -greedy market-selection strategy is removed because the reputation approach deals with this separately (Section 6.8); and (ii) no reward signals are provided. Rather, each day, the market-exchange with the highest reputation is joined with probability  $\varepsilon$  and a random exchange with probability  $1 - \varepsilon$ .

## 6.3 Modelling Uncertain Market-based Environments

This section is motivated by: (i) a desire to empirically evaluate the appropriateness of reputation approaches for facilitating market-selection decisions in a multi-attribute model of resource allocation; and (ii) noting that, as defined in the previous section, the accuracy of reputation information is dependent upon other agents' opinions being accurate. While subjective Bayesian approaches [165, 96] have been proposed to deal with inaccurate reputation information, they have not been applied in this type of domain, which, as will be described, may contain different types of agent behaviour. This section extends the multi-attribute market-based model developed in this thesis by introducing some of these agent behaviours, so that they can then be incorporated into simulations to evaluate the appropriateness of subjective



Bayesian approaches to reputation in this type of market-based model. In line with the literature [43, 79, 165, 96], we focus on both strategic and non-strategic non-conformist agent behaviours, but identify how they differ in this model to others.

### 6.3.1 Noisy recommenders

Incorrect opinions (or recommendations), i.e., those that differ from reality, are clearly a problem for the accuracy of reputations, which can lead to poor decision making. *Noisy Recommenders* represent traders whose publicly distributed opinion are: (i) random in nature and likely to differ from their true opinions of the market-exchanges they are distributing recommendations about; and (ii) likely to be provided to all agents *indiscriminately*. That is to say, all traders will receive the same information. Noisy Recommenders represent traders that might, for example: (i) have software faults; (ii) have some process acting on the inter-agent communication protocol that results in their opinions being corrupted; or (iii) be programmed to specifically attempt to distort the reputation system, but without bias to any type of trader. Noisy recommenders are represented as a subset of all traders:  $\mathcal{T}^{\text{NR}} \subset \mathcal{T}$ . When a noisy recommender  $a_i \in \mathcal{T}^{\text{NR}}$  is asked by another trading agent  $a_j \in \mathcal{T}$  for its opinion  $\tau_{a_i, m_k}$  of market-exchange agent  $m_k$ , the opinion it provides, in the form of  $\alpha$  and  $\beta$  values, is generated in a stochastic way. Firstly, randomised *bias*  $\dot{\mu}$  and *scale*  $\dot{\sigma}$  values are drawn from uniform distributions:

$$\begin{aligned}\dot{\mu} &= \text{U}(0, 1) \\ \dot{\sigma} &= \text{U}(\dot{\sigma}_{\min}, \dot{\sigma}_{\max}),\end{aligned}\tag{6.12}$$

where  $0 < \dot{\sigma}_{\min} \leq \dot{\sigma}_{\max}$ .  $\dot{\mu}$  represents the type of opinion that  $a_i$  will give regarding market-exchange  $m_k$ . The larger the value  $\dot{\mu}$  takes, the higher the opinion of  $m_k$  that  $a_i$  communicates.  $\dot{\sigma}$  represents the *strength* of the opinion. The larger the value  $\dot{\sigma}$  takes, the more *confidence*  $a_i$  states it has in its opinion of

### 6.3. MODELLING UNCERTAIN MARKET-BASED ENVIRONMENTS

market-exchange  $m_k$ .  $a_i$  will provide its opinion in the form of an  $\alpha$  and  $\beta$  pair, calculated as follows:

$$\begin{aligned}\dot{\alpha}_{a_i, m_k} &= 1 + \dot{\mu} \times \dot{\sigma} \\ \dot{\beta}_{a_i, m_k} &= 1 + (1 - \dot{\mu}) \times \dot{\sigma}\end{aligned}\tag{6.13}$$

While, other models for evaluating Bayesian reputation approaches [166, 165, 96] consider noisily reported information, it is applied using Gaussian noise centred in their *true* opinion. While this may be appropriate in the environments they consider, e.g., when modelling communication noise or mild data corruption, because the opinions are in expectation truthful, they don't model well many potential types of faulty agent. The definitions above ensure opinions provided by noisy recommenders are entirely random, rather than simply noisy versions of truthful information, which more closely models, for example, bugs in software code, which rarely result in Gaussian perturbations of truthful opinions.

#### 6.3.2 Lying recommenders

As well as non-strategic noisy recommenders, agents often receive strategic opinions (recommendations) based on *malicious information*. Malicious opinions are those that are provided purposely, and in an attempt to *alter* decisions of other traders such that one's own prospects are improved. Inaccurate opinions are often provided for two reasons: (i) through the distribution of unfairly low ratings, otherwise known as 'bad-mouthing'; and (ii) through the distribution of unfairly inflated high ratings [43]. Jin et al. [79] describes two different types of lying that a malicious agent might perform, within a multi-agent reputation system: (i) *Destructive lying* is a complementary strategy, i.e., one in which agents always provide opinions contrary to the reality they have experienced; and (ii) *Collusive lying*, where malicious agents form a cohort that attempts to reduce the reputation of other competing agents, by spreading incorrect opinions in unison. These types of lying behaviour are quite general, and can be applied to many open multi-agent systems. However, lying agent's strategies may be

different in a market-based system, particularly because strategic traders rely on the decisions of other traders in order to trade, and thus maximise profit.

Therefore malicious behaviour, specific to market-based systems with two-sided markets, needs to be considered.

### The Supply and Demand Attack

Supply and demand in a market run by one of the market-exchanges will significantly affect traders' transaction prices. A reduction in the number of buyers within a market, for example, will result in reduced demand for the resource within that market, lowering transaction prices—a desirable situation for buyers. Alternatively, an increase in the number of buyers (or a reduction in the number of sellers), resulting in an increase in demand (or reduction in supply), will tend to increase transaction prices within the market—a desirable situation for sellers.

The *Supply and Demand Attack* occurs when a trader  $a_i$  specifically decides what type of opinion to provide to a requesting trader  $a_j$ , by considering whether  $a_j$  is a *competitor* to  $a_i$ . The aim of this strategy is to *alter* the supply and demand within a market, in the hope that the *price* of resources in the market becomes more favourable for the attacker. Consider, as described in Chapter 5, a trader context  $\mathcal{T}$  made up of populations of traders with different preferences and/or constraints. As previously discussed, cohorts of these traders will form *market segments*, and prefer to trade the same resources, which will, when market niching is occurring, be provided by a market-exchange's market. While traders previously only used private information to make market-selection decisions, with a reputation approach some traders could strategically attempt to either attract or repel certain types of traders to or from the market they are trading in; particularly if they had ways of identifying them easily.

Next, consider three trading agents  $a_1$ ,  $a_2$  and  $a_3$ , each of which are members of a subset  $\mathcal{T}_1$  of traders occupying the same market segment, indicating

### 6.3. MODELLING UNCERTAIN MARKET-BASED ENVIRONMENTS

the traders prefer to trade the same resources. Two traders ( $a_1$  and  $a_2$ ) are buyers, while the other ( $a_3$ ) is a seller. Each agent would prefer to join the same resource markets, and, in a longterm cooperative manner, each would be better off by sharing information about market-selection with each other, hopefully encouraging more traders in the segment to join and creating a healthy market. Assume that  $a_1$  is asked by  $a_2$  and  $a_3$  for its opinion of market-exchange  $m_k$ . If one assumes that  $a_1$ , a buyer, is aware that  $a_2$  is a buyer and that  $a_3$  is a seller, if  $a_1$  was using the supply and demand attack strategy, it would provide a truthful opinion to  $a_3$ , and a malicious and dishonest opinion to  $a_2$ . Thus, the intended result of the supply and demand attack, is to encourage traders you wish to trade with—buyers try and attract sellers, seller try and attract buyers—to the same market as you (by supplying truthful opinions), and to discourage *competing* traders from joining the same market as you, with the intention of altering the supply or demand in your favour. More formally, a trader  $a_i$  who is using the *Supply and Demand Attack* will provide an opinion to another trader  $a_j$ , regarding market-exchange  $m_k$ , in the form of  $\ddot{\alpha}$  and  $\ddot{\beta}$  values, as follows:

$$\begin{aligned} \ddot{\alpha}_{a_i, m_k} &= \begin{cases} \beta_{a_i, m_k} & \text{if } \{a_i, a_j\} \subset \mathcal{T}_s \wedge ((\{a_i, a_j\} \subset \mathcal{B}) \vee \{a_i, a_j\} \subset \mathcal{S})) \\ \alpha_{a_i, m_k} & \text{otherwise} \end{cases} \\ \ddot{\beta}_{a_i, m_k} &= \begin{cases} \alpha_{a_i, m_k} & \text{if } \{a_i, a_j\} \subset \mathcal{T}_s \wedge ((\{a_i, a_j\} \subset \mathcal{B}) \vee \{a_i, a_j\} \subset \mathcal{S})) \\ \beta_{a_i, m_k} & \text{otherwise} \end{cases} \end{aligned} \quad (6.14)$$

where  $\mathcal{B}$  and  $\mathcal{S}$  are the sets of all buyers and sellers respectively, and  $\mathcal{T}_s$  refers to a subset of traders all interested in the same type resource type, and thus from the same market segment  $s$ . Thus,  $a_i$  provides either honest opinions to a trader who it may wish to trade with (or who poses no competitive threat), and dishonest opinions to those traders who are directly competing over the same resources; as shown in Equation 6.14, dishonest opinions are provided in the form of *opposite* opinions.

### 6.3.3 Trader churn

Trader churn is an important aspect of the extension to Chapter 4's model considered in this chapter. In many multi-agent systems, agent churn is a reality, as agents leave and join the system. In P2P systems, the notion of *node churn* has been well studied [162, 161], with overall conclusions suggesting that it is an important aspect of any dynamic system, which should be considered when designing multi-agent systems [36].

However, subjective Bayesian reputation approaches have not yet considered the impact that trader churn within a market-based system might have on the effectiveness of the reputation mechanism. Trader churn may have a significant impact on the performance of the system. In other applications it is often the case that all agents are either universally good or bad, thus, when a new agent joins the system it can be given reputation information informing it of the bad agents to avoid (either interacting with, or using opinions of). However, in this system new agents have to learn, via reputation information, more subtle differences, such as that some markets may be good to one trader, but the same market bad to another. Therefore, it is important that the reputation approach can accurately provide *useful* information to newcomers in the system, as well as be *robust* to information loss from traders leaving. Trader churn describes the process of traders entering and leaving the system over time. Specifically trader churn is defined in this model as:

- *Trader Entry*: when *new* traders enter the system with a lack of any knowledge about the behaviour of other traders, and thus have uncertain market-selection signals;
- *Trader Exit*: when traders who have spent time interacting with other traders and market-exchanges in the environment leave the system. Importantly, when these traders leave, all the private information they have on market-exchanges is also removed from the system.

## 6.4 A Subjective Reputation Approach for Uncertain Environments

Section 6.2 described an *objective* reputation system. Unlike some applications where an *objective* reputation system is applicable [120, 121, 98, 188], it is hypothesised that in a multi-attribute market-based system, an objective reputation system will not be as effective as a subjective reputation system. In any marketplace where consumer preferences differ, *subjective* reputation mechanisms should be more advantageous, because they consider agents' preferences when forming reputations. This section considers subjective Bayesian reputation approaches [166, 165, 97], and applies them within the context of this market-based model, so that the effectiveness of this approach can be evaluated in the next section. In this model, there are two main reasons why a subjective approach is important:

- *Heterogenous trader types*: some traders, due to preferences or constraints on attributes, will not be interested in the same resources. While one market-exchange may be held in high regard by one portion of the trader population, it may not be in other sections or segments of the trader population. Unfortunately, market-exchange reputations in an objective system are equivalent across traders.
- *Inaccurate Recommendation Information*: again, because all opinions are considered equally when forming objective reputations, it is not possible to distinguish between accurate and inaccurate opinions, which can lead to undeserved poor reputations [5], or likewise inflated good reputations [43].

Thus, a mechanism is needed to help each trader learn which other traders' opinions it should incorporate into market-exchange reputations, and to what degree each should be weighted.

### 6.4.1 Recommendation weights for trader opinions

As previously defined in Equation 6.9, a trader generates a reputation of a market-exchange in the form of a beta distribution that combines multiple

distributions, based on other traders' interaction histories. By using a *recommendation weight*—in the form of the function  $\varphi(a_i, a_j)$ —that defines how useful trader  $a_i$  considers trader  $a_j$ 's opinions to be, trader  $a_i$  can calculate a *personal* and *subjective* distribution to describe market-exchange  $m_k$ , as shown in Equation 6.15.

$$\begin{aligned}\alpha_{a_i, m_k}^{rep, t} &= \sum_{j=1, j \neq i}^{|\mathcal{T}|} \varphi(a_i, a_j) \left[ \alpha_{a_j, m_k}^t - 1 \right] \\ \beta_{a_i, m_k}^{rep, t} &= \sum_{j=1, j \neq i}^{|\mathcal{T}|} \varphi(a_i, a_j) \left[ \beta_{a_j, m_k}^t - 1 \right]\end{aligned}\quad (6.15)$$

The reputation  $\rho_{a_i, m_k}^t$ , which represents the reputation of market-exchange  $m_k$ , from the perspective of  $a_i$  can be calculated in the same way as it was initially, in Equation 6.10 on Page 186, but with  $\alpha_{a_i, m_k}^{rep, t}$  and  $\beta_{a_i, m_k}^{rep, t}$  defined according to Equation 6.15. While Equation 6.15 still *considers* all publicly available information, unlike the objective version, each opinion is weighted independently. Some opinions are likely to be so unhelpful that their inclusion in the calculation of  $\rho_{a_i, m_k}^t$  would not help trader  $a_i$  at all. A trader can *exclude* these opinions from the calculation of  $\alpha_{a_i, m_k}^{rep, t}$  and  $\beta_{a_i, m_k}^{rep, t}$ , by giving them a recommendation weight of zero, as follows:

$$\varphi(a_i, a_j) = \begin{cases} \widehat{\gamma}_{a_i, a_j} & \text{if } \widehat{\gamma}_{a_i, a_j} \geq \widehat{\gamma}_{a_i}^* \\ 0 & \text{otherwise} \end{cases}\quad (6.16)$$

As one can see from Equation 6.16, the actual recommendation weight from trader  $a_i$  to trader  $a_j$  is represented by  $\widehat{\gamma}_{a_i, a_j}$ , and the function  $\varphi(a_i, a_j)$  either returns  $\widehat{\gamma}_{a_i, a_j}$  if it exceeds a minimum threshold  $\widehat{\gamma}_{a_i}^*$ , or zero otherwise; thus, traders in the system must have a recommendation weight of at least  $\widehat{\gamma}_{a_i}^*$  for trader  $a_i$  to consider their opinions at all.

### 6.4.2 Learning recommendation weights

Next, how a trader *learns*  $\widehat{\gamma}_{a_i, a_j}$  over time, is described. As with the rest of the Bayesian reputation approach, one can use a Beta distribution to model the process that describes the probability of trader  $a_i$  receiving a *useful* opinion from a trader  $a_j$ , and set  $\widehat{\gamma}_{a_i, a_j}$  as the expected value of this distribution. When  $a_i$  built trust  $\tau_{a_i, m_k}$  in market-exchange  $m_k$ , it updated  $\alpha_{a_i, m_k}$  and  $\beta_{a_i, m_k}$  according to the outcome  $o_{a_i, m_k}$  of interactions with  $m_k$ . It does something similar to update  $\widehat{\gamma}_{a_i, a_j}$ , by updating  $\widehat{\alpha}_{a_i, m_k}$  and  $\widehat{\beta}_{a_i, m_k}$  according to how useful an opinion given by another trader  $a_j$  was. To do this, however, one needs to *quantify* what *useful opinion* means. Liu and Issarny [97, 96] describe a technique for quantifying whether an opinion was useful, which is adapted for this model, though with new notation applied. The technique works as follows: once a trader  $a_i$  has interacted with a market-exchange  $m_k$  at time  $t$ , it takes each of the independent opinion distributions it received from other traders at time  $t - 1$ , and *measures* how accurately those opinion distributions each *predicted* the outcome of the interaction  $a_i$  had with  $m_k$ . From Equation 6.5, it is known that an outcome between  $a_i$  and  $m_k$  depends on whether or not  $a_i$  traded and made a profit on the exchange, and is the form  $o_{a_i, m_k} \in \{0, 0.5, 1.0\}$ . Therefore, to measure how accurately an opinion from trader  $a_j$  to  $a_i$  at time  $t - 1$  predicts  $o_{a_i, m_k}^t$ , one sees how much of  $f(p|\alpha_{a_j, m_k}^{t-1}, \beta_{a_j, m_k}^{t-1})$  falls into the range  $[o_{a_i, m_k}^t - \varepsilon_{a_i}, o_{a_i, m_k}^t + \varepsilon_{a_i}]$ , as follows:

$$\begin{aligned} \Lambda_{a_i, m_k}^{a_j, t} &= \frac{\int_{\max(o_{a_i, m_k}^t - \varepsilon_{a_i}, 0)}^{\min(o_{a_i, m_k}^t + \varepsilon_{a_i}, 1)} u^{\alpha_{a_j, m_k}^{t-1} - 1} (1 - u)^{\beta_{a_j, m_k}^{t-1} - 1} du}{\int_0^1 u^{\alpha_{a_j, m_k}^{t-1} - 1} (1 - u)^{\beta_{a_j, m_k}^{t-1} - 1} du} \\ &= I_{o_{a_i, m_k}^t + \varepsilon_{a_i}}^t(\alpha_{a_j, m_k}^{t-1}, \beta_{a_j, m_k}^{t-1}) - I_{o_{a_i, m_k}^t - \varepsilon_{a_i}}^t(\alpha_{a_j, m_k}^{t-1}, \beta_{a_j, m_k}^{t-1}) \end{aligned} \quad (6.17)$$

In Equation 6.17,  $\Lambda_{a_i, m_k}^{a_j, t}$  measures the probability of an interaction outcome  $o_{a_i, m_k}$  between  $a_i$  and  $m_k$ , falling in the range  $[o_{a_i, m_k} - \varepsilon_{a_i}, o_{a_i, m_k} + \varepsilon_{a_i}]$ , according to the opinion provided by trader  $a_j$ . The term  $I_{o_{a_i, m_k}^t}^t$  is the Regularised Incomplete Beta



Function, which is the cumulative distribution function for the Beta distribution. Calculating  $\Lambda_{a_i, m_k}^{a_j, t}$  forms only part of the technique for measuring the usefulness of  $a_j$ 's opinion. Next,  $\Lambda_{a_i, m_k}^{a_j, t}$  is compared to the probability of  $o_{a_i, m_k}^t$  falling into the range  $[o_{a_i, m_k}^t - \varepsilon_{a_i}, o_{a_i, m_k}^t + \varepsilon_{a_i}]$  according to the *prior* beta distribution, which we measure as:

$$\Lambda_{a_i, m_k}^{min, t} = I_{o_{a_i, m_k}^t + \varepsilon_{a_i}}^t(1, 1) - I_{o_{a_i, m_k}^t - \varepsilon_{a_i}}^t(1, 1) \quad (6.18)$$

$\Lambda_{a_i, m_k}^{a_j, t}$  and  $\Lambda_{a_i, m_k}^{min, t}$  can then be compared to ascertain just how useful trader  $a_j$ 's opinion was:

$$\widehat{o}_{a_i, m_k}^{a_j, t} = \max(\min(\Lambda_{a_i, m_k}^{a_j, t} - \Lambda_{a_i, m_k}^{min, t} + 0.5, 1.0), 0.0) \quad (6.19)$$

Equation 6.19 ensures that the usefulness of an opinion,  $\widehat{o}_{a_i, m_k}^{a_j, t}$ , from trader  $a_j$  to  $a_i$ , regarding  $m_k$ , falls in the range  $[0, 1]$ . If  $\Lambda_{a_i, m_k}^{a_j, t} > \Lambda_{a_i, m_k}^{min, t}$  then trader  $a_i$  can treat trader  $a_j$ 's opinion as useful, since it provides a more accurate probability of  $o_{a_i, m_k}^{t-1}$  falling into the range  $[o_{a_i, m_k}^t - \varepsilon_{a_i}, o_{a_i, m_k}^t + \varepsilon_{a_i}]$  than the prior beta distribution; in such a case  $\widehat{o}_{a_i, m_k}^{a_j, t} > 0.5$ . On the other hand, if it is the case that  $\Lambda_{a_i, m_k}^{a_j, t} < \Lambda_{a_i, m_k}^{min, t}$  then  $a_j$  has provided an opinion to  $a_i$  that is *less* useful than the one that would be provided by the prior distribution, viz the reputation for  $m_k$  formed by  $a_i$  using information from  $a_j$  would have been more accurate if  $a_i$  had *excluded* the opinion from  $a_j$ ; in such a case  $\widehat{o}_{a_i, m_k}^{a_j, t} < 0.5$ . Finally, if the opinion from  $a_j$ 's distribution is equally useful to the usefulness of one from a prior distribution then  $\widehat{o}_{a_i, m_k}^{a_j, t} = 0.5$ . Once the usefulness of an opinion  $\widehat{o}_{a_i, m_k}^{a_j, t}$  has been calculated, it can be used to update the shape parameters  $\widehat{\alpha}_{a_i, a_j}$  and  $\widehat{\beta}_{a_i, a_j}$  for the beta distribution that is being used to provide  $a_i$ 's recommendation weight for  $a_j$ :

$$\begin{aligned} \widehat{\alpha}_{a_i, a_j}^{t+1} &= \widehat{\alpha}_{a_i, a_j}^t + \widehat{o}_{a_i, a_j}^t \\ \widehat{\beta}_{a_i, a_j}^{t+1} &= \widehat{\beta}_{a_i, a_j}^t + 1 - \widehat{o}_{a_i, a_j}^t \end{aligned} \quad (6.20)$$

Thus, this distribution is updated in the same way as the one that is used for calculating trust values in Equation 6.6 on Page 182. Finally, the recommendation

#### 6.4. A SUBJECTIVE REPUTATION APPROACH FOR UNCERTAIN ENVIRONMENTS

weight that trader  $a_i$  maintains for trader  $a_j$ , in terms of the expected value of the beta distribution formed from  $\hat{\alpha}_{a_i,a_j}$  and  $\hat{\beta}_{a_i,a_j}$  can be defined:

$$\hat{\gamma}_{a_i,a_j} = E[p_{a_i,a_j} | \hat{\alpha}_{a_i,a_j}, \hat{\beta}_{a_i,a_j}] = \frac{\hat{\alpha}_{a_i,a_j}}{\hat{\alpha}_{a_i,a_j} + \hat{\beta}_{a_i,a_j}}, \text{ where } \hat{\alpha}_{a_i,a_j}, \hat{\beta}_{a_i,a_j} > 0 \quad (6.21)$$

Recall that when using the objective reputation system in Section 6.2, a trader uses only *trust* as its market-selection signal, if it believes that it has enough confidence in its trust value of a market-exchange, which is based on information gathered from previous direct interactions (Equation 6.7). If it finds that it is not confident enough in its own trust value, it will seek the opinions of others, and form a reputation value by combining others' opinions with its own trust, which will then be used as the market-selection signal. In order to decide whether to use reputation in market-selection signal formation, a parameter  $\gamma_{a_i}^*$  representing the confidence threshold trader  $a_i$  needs to be set. Using the subjective approach, however, this parameter can be removed from the system, and replaced by  $\hat{\gamma}_{a_i}^*$ , which sets the threshold at which opinions are *excluded*. By *always* considering other traders' opinions, and using  $\varphi(a_i, a_j)$  to decide on their inclusion (and to what degree of influence), a trader does not need to make an either/or decision between its own direct information and publicly available information, but can make a more *fine-grained* decision, which can be based on *some* public information, rather than based on no public information or all of it. In terms of the subjective reputation system, once reputation  $\rho_{a_i,a_j}^t$  has been formed in Equation 6.10, using the subjectively weighted values from Equation 6.15 the market-selection signal simply becomes:

$$\zeta_{a_i,a_j}^t = \rho_{a_i,a_j}^t \quad (6.22)$$

Given this approach, the decision step involving whether to use exclusively trust or reputation is removed, and they will be combined when making market-selection decisions. Trust based on direct interactions always has a

recommendation weight of 1.0, however the constant adjusting of recommendation weights for the other traders means that the influence of reputation information on market-selection can be adapted over time, according to the environmental situation. This section concludes with an example of the difference a subjective reputation system approach can make over an objective one. In Figure 6.2 on Page 185, four separate beta distributions (three of which were opinions from other traders) were objectively aggregated to form a reputation using a combined Beta distribution, the expected value of which was the objective reputation value. In Figure 6.3, the same four distributions are assumed but with recommendation weights associated with them. The prior distribution shown in this example belongs to the trader  $a_i$  seeking opinions, thus it has a recommendation weight  $\hat{\gamma}_{a_i, a_i} = 1.0$ . Figure 6.3a plots the various beta

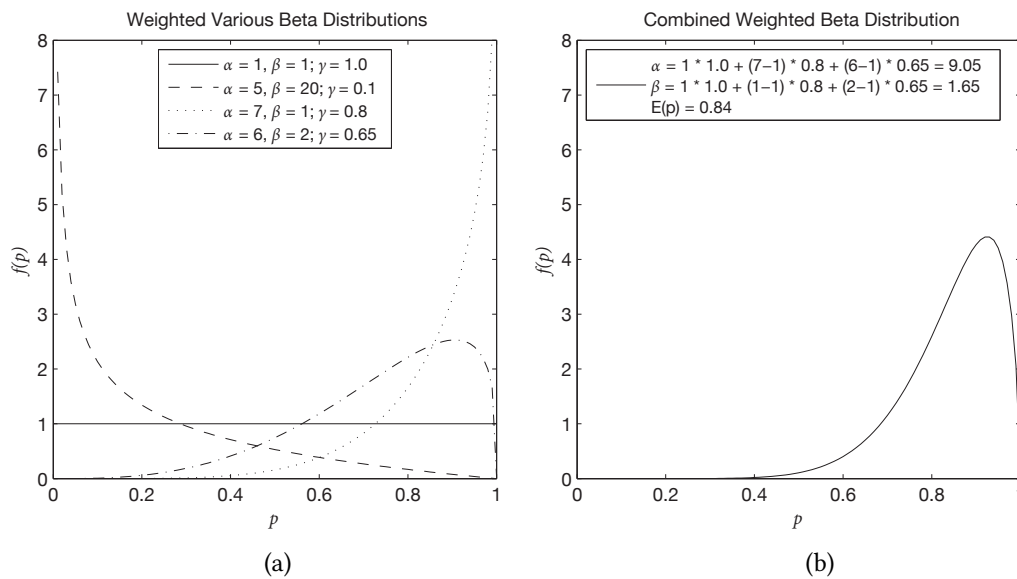


Figure 6.3: The same collection of beta distributions as first shown in Figure 6.2a (Page 185) but *weighted* according to recommendation weights  $\hat{\gamma}$ . Note that when combined, one of the distributions is disregarded in the calculation, due to its  $\hat{\gamma} = 0.1$  value being below a threshold value (set at  $\hat{\gamma}^* = 0.65$ ). The resulting distribution has a high expected value of 0.84, unlike the unweighted one in Figure 6.2b, which has an expected value of 0.43.

distributions formed from  $a_i$ 's unknown prior distribution, and the opinions of the other traders, weighted by the associated recommendation weights. Unlike

## 6.5. AN EMPIRICAL ANALYSIS OF REPUTATION APPROACHES

the distributions in Figure 6.2a, the recommendation weights move the distributions closer to the unknown prior distribution by an amount *proportional* to their recommendation weight. When these distributions are combined, one of them is ignored because their recommendation weight does not exceed the recommendation threshold—in this example  $\gamma_{a_i}^* = 0.65$ . The remaining two opinion distributions, and the trust distribution, which is the prior, due to  $a_i$ 's lack of direct interactions with the market-exchange in question, are combined to form the overall reputation distribution in Figure 6.3b. In this example, the market-selection signal  $\varsigma_{a_i, m_k} = \rho_{a_i, m_k} = E[p_{a_i, m_k} | \hat{\alpha}_{a_i, m_k}, \hat{\beta}_{a_i, m_k}] = 0.84$ , which is in stark contrast to the objective reputation information, where all available sources were included, resulting in  $\varsigma_{a_i, m_k} = 0.43$ .

## 6.5 An Empirical Analysis of Reputation Approaches

In this section, both the objective and subjective Bayesian reputation approaches described in this chapter are empirically assessed within a variety of environmental contexts. Experiments in Section 6.5.1 concern the impacts of trader churn on the system, and the impact a basic objective Bayesian approach has. In Sections 6.5.2 and 6.5.3 false reporting is considered, in terms of the two recommender behaviour models previously introduced, and a subjective reputation approach is compared to an objective approach. Finally, in Section 6.5.4 an initial statistical analysis is carried out on the formation and emergence of recommendation networks between traders.

### 6.5.1 The effects of trader churn on system performance

This section addresses the following research question:

*What impact does trader churn have on traders' profitability and the overall allocative efficiency in the system, and to what extent can reputation information improve these metrics?*

This set of experiments is concerned with the impact that trader churn, as described in Section 6.3.3, has on the allocative efficiency of the market-based system under two experimental variants: (i) when traders use the  $\epsilon$ -greedy market-selection strategy that uses private historical profit; and (ii) when traders use the *reputation-based* market-selection strategy defined in Section 6.2.3, on Page 186. Recall that some unsuitable market-exchanges, e.g., those whose resource markets don't satisfy constraints, will be considered *inept* and not make it into traders' consideration sets. However, a trader needs time to learn which of the exchanges that are in the consideration set will result in the most profitable trades when joined. In a large system, with many competing market-exchanges in the environment, one would imagine several market-exchanges would end up competing over market niches, resulting in traders having many choices in their consideration sets. For a new trader—a *newcomer*—learning which of these exchanges would be most profitable to join takes time, and without any form of public information about previous trader profits made in the markets, newcomer trading agents will likely make costly mistakes learning which of the market-exchanges are most profitable. Based on this reasoning, the following hypothesis is formed:

**Hypothesis 6.1.** *Allocative efficiency will be higher when traders have access to the reputations of market-exchanges, because reputation information provides a market-selection signal to traders, which in the absence of reputation they would otherwise have to spend time learning directly.*

### Experimental setup

Hypothesis 6.1 is tested using the following simulation environment. To simulate the scenario of multiple exchanges competing over the same niche, *nine* market-exchanges are simulated. To simplify analysis, each market-exchange provides the same market for trading resources with attribute-levels of  $\pi = \langle 1.0, 1.0 \rangle$ . However, each exchange has different charging schemes. Results in Chapter 5 suggested that it is difficult to correlate explicit charges and fees with

6.5. AN EMPIRICAL ANALYSIS OF REPUTATION APPROACHES

Number of Market-exchanges	Registration Fee	Transaction Fee	Bid/Ask Commission
3	0.01	0.01%	0.0%
3	0.05	0.02%	0.0%
3	0.02	0.03%	0.0%

Table 6.1: Three types of charging scheme were split equally across nine market-exchanges. For more details on charging schemes see Section 4.1.1, on Page 85. While it may seem intuitive that the cheapest market-exchange is best to join, Shi et al. [154] has shown that there exist Nash equilibria in environments with competing marketplace where all traders migrate to more expensive markets. It is therefore non-trivial for a trader to know initially which market-exchange is best to join each day.

how profitable a market may be. Many other factors effect market-selection, and because one market-exchange is cheaper than others, does not mean that it will be the best market to join [154], because complex dynamics based on the volumes of traders within each market affect where they migrate to, and thus which market is most profitable. Therefore, it is non-trivial for a trader to know initially which market-exchange is best to join each day. Table 6.1 provides details of how charging schemes were instantiated on market-exchanges. For these simulations the *unconstrained single niche* defined in Section 5.3.1 (Page 135) was used, which meant all exchanges and traders competed over the same market niche. At all times there were 300 traders within the system; every time a new trader joined the system, a trader was randomly selected to leave the system. Each *newcomer* trader was randomly initialised according to the same parameters as the other traders, i.e., with budgets constraints in the same range. Each simulation lasted for 5000 trading days, and was repeated 50 times. For this analysis the distributed nature of traders, and that they may not be able to communicate with all others is not considered; thus, when calculating reputations, all traders can access all others' opinions. Further, this set of experiments only concerns itself with the impact of churn, thus there are no noisy recommenders or lying agents in the system. The exploration parameter used in both the *reputation-based* and private value based market-selection strategies was set to the most common value

$\varepsilon = 0.1$ .

### Experimental results

Hypothesis 6.1 was tested by running two sets of experimental simulations. In the first set, traders use the  $\varepsilon$ -greedy strategy to learn market-selection signals based upon their historical profit in markets. In the second set of simulations the traders used the *reputation-based* market-selection strategy (Section 6.2.3), where they choose between market-exchanges by calculating their reputations from asking other traders within the system. Both sets of experiments were executed with varying levels of *trader churn* in the system, ranging from 0%–10%. The same level of churn was maintained for the duration of a simulation. Figure 6.4 shows the

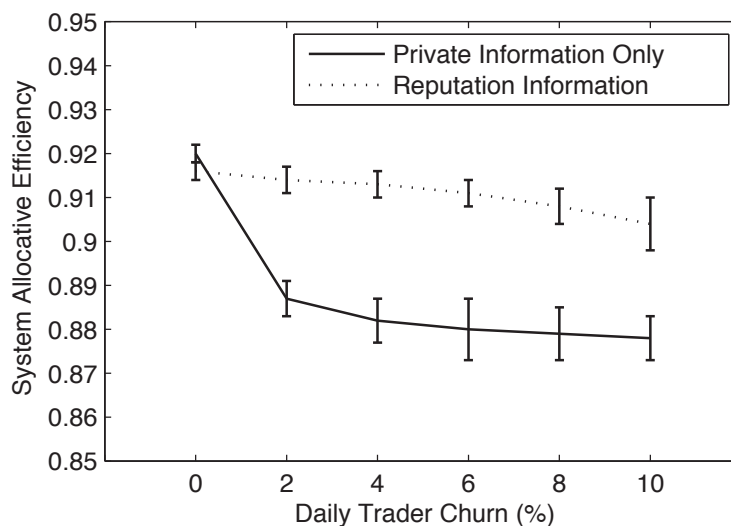


Figure 6.4: Overall mean system allocative efficiency for varying levels of trader churn. Each point represents the mean system efficiency resulting from the type of simulation defined by the churn rate ( $x$  axis). ‘Private Information Only’ refers to simulation where traders can only use their own profit information to make market-selection decisions, while ‘Reputation Information’ refers to simulations where traders can ask other traders for opinions on market-exchanges, and use the resulting reputations to make market-selection decisions. As the plot shows, in the absence of any reputation information to form a market-selection signal for new traders, allocative efficiency is reduced as the proportion of new traders increases. Allocative efficiency is measured using the algorithm defined in Chapter 4.

impact that both *trader churn* and the presence or absence of reputation has on the allocative efficiency of the system; there are a number of interesting

## 6.5. AN EMPIRICAL ANALYSIS OF REPUTATION APPROACHES

observations. Firstly, in the absence of churn, both private information and reputation information based approaches lead to allocations with similar efficiencies: 92% and 91.6% respectively. A t-test of equality of means<sup>1</sup> returns a  $p\text{-value} < 0.005$ , which although significant, the performance between the two is very close with only a 0.4% difference in efficiency. This result is not surprising, because private direct information is always more accurate, and in the absence of churn traders can recoup the cost of learning, but the reputation approach certainly does not *substantially* reduce the efficiency of allocations. However, as the experimental variations are run with increasing levels of daily churn, the detrimental affect that trader churn has on the allocative efficiency of the system becomes apparent. Even at low levels of churn, if newcomer traders can leverage reputation information, they can locate the best markets faster, and much more efficient allocations are observed. There is a clear statistical significance between the two setups for the 2–10% churn cases; for example, a t-test of equality of means for the 10% case returns a  $p\text{-value} < 0.005$  and a  $t\text{-value}$  of 15.11. When reputation is available, newcomer traders can quickly be notified via other traders' opinions, which of the exchanges are the best to join, which leads to more traders trading in the same market, and thus more efficient outcomes. While the trend in Figure 6.4 suggests that increases in churn always affects efficiency, this is likely because the dynamics created by traders joining and leaving can affect the equilibrium price of the market, which the traders must learn to adapt to, using their ZIP pricing algorithms.

Finally, Figure 6.5 shows the impact that trader churn has on the proportion of system profits the traders keep, in the absence of presence of reputation. While the manner in which the total utility—measured as profit—of an allocation is split between exchanges and traders does not affect that allocation's efficiency, it is of interest to know what impact the reputation approach has on traders' share of system profits. In the absence of reputation, trader profit-share drops as churn

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<sup>1</sup>All simulation allocative efficiency data samples tested within this chapter were found to be normally distributed.



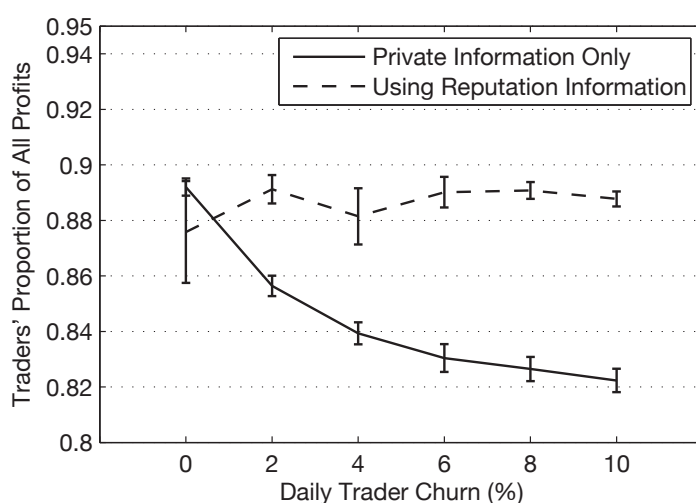


Figure 6.5: Given the overall mean system utility, as measured in profits, this figure shows the *proportion* of total system profits kept by the trader population. The remainder of the profits are taken by the market-exchanges through fees and charges. When the traders use the reputation approach to market-selection, they join the more profitable markets faster, because they use others' opinions to form market-exchange reputations. As the simulations are repeated with increasing levels of churn, trader profits are generally maintained at the same level in the reputation approach. However, in the absence of reputation the impact of newcomer traders making costly mistakes exploring different market becomes apparent.

increases, consistent with newcomer traders joining expensive markets or ones they can't trade in—part of the private learning process. With the reputation approach, however, there is no distinguishable drop in trader profit-share as churn increases because market-selection signals can be provided by reputation information.

### 6.5.2 Dealing with noisy recommenders

In this and the next sections, comparisons between a subjective and objective reputation approach and are made. Of particular interest is how each of these approaches deal with: (i) different types of recommender traders; and (ii) trader contexts with traders that have different preferences and constraints over resources, and thus prefer different niches. The following research questions are of immediate interest:

## 6.5. AN EMPIRICAL ANALYSIS OF REPUTATION APPROACHES

- *How well do objective and subjective reputation approaches provide market-selection signals to traders in multi-niche environments?*
- *What impact do increasing levels of noisy recommenders have on resource allocations when objective and subjective reputation approaches are utilised?*

Traders who are satisfied by different market niches will prefer to trade in different resource markets. Therefore, positive or negative opinions may be helpful or unhelpful to different traders in a multi-niche environment.

**Hypothesis 6.2.** *Market-selection signals that are formed using a subjective reputation approach will be more accurate than those formed using an objective reputation approach, because traders can subjectively adjust the importance of different traders' opinions in forming market-selection signals.*

And, in terms of the second research question above:

**Hypothesis 6.3.** *In the presence of noisy recommenders, resource allocations will always be more efficient when market-selection signals are formed using a subjective approach, because it enables traders to identify noisy recommenders and ignore their opinions.*

### Experimental setup

This section is concerned with environments where reputation approaches are assumed to be required, and is investigating differences between an objective and subjective approach. In adherence, the system is assumed to have a reasonable amount of churn (10%) at all times. Further, in the spirit of extending the previous Chapter's work, market-exchanges are now able to adjust their attribute-levels, in this case using  $\epsilon$ -greedy attribute-level selection strategies. Again, nine market-exchanges are considered, with the same charging schemes in Table 6.1. In terms of traders, the *constraint-induced niches* trader context (Section 5.3.1, Page 135), where there are multiple niches, is used. Therefore, in this set of experiments, nine market-exchanges are adapting in an attempt to find market niches within an environment where 300 traders have potentially different preferences and constraints over resources, creating dynamic environments and difficult market-selection decisions for new traders.

Noisy recommenders are chosen randomly at initialisation time. If a noisy recommender leaves the system it is replaced by a new one; further, a new trader has the same preferences and constraints as the one its replaces, but a randomly generated budget constraint. Noisy recommenders use:  $\dot{\sigma}_{min} = 10$ ,  $\dot{\sigma}_{max} = 30$ , which allowed for reasonably strong opinions. The Bayesian reputation mechanism's parameters, after some initial exploratory simulations, were chosen inline with other studies that have made use of similar Bayesian approaches [97]. Traders discount their opinions according to  $\Delta t = 0.95$ ; confidence bounds on Beta distributions are measured using  $\varepsilon = 0.4$ ; when using the objective approach the confidence threshold  $\gamma_{a_i}^* = 0.6$ , while for the subjective approach the recommendation weight threshold, used to indicate when to completely ignore an agent's opinions was set to  $\widehat{\gamma}_{a_i}^* = 0.6$ .

### Experimental results

Each data point reported is the mean value from 50 simulation repetitions. We first test Hypothesis 6.2 by comparing allocative efficiency values for two experimental variations: one using the objective reputation approach in Section 6.2, and one using the subjective approach described in Section 6.4. When traders used the objective approach and there were no noisy recommenders, mean allocative efficiency was  $44.0\% \pm 3.9\%$  versus  $66.1\% \pm 3.7\%$  when the subjective system was in place. A t-test of equality of means resulted in a *p-value*  $< 0.005$ , thus these means are statistically distinct and Hypothesis 6.2 can be accepted. Figure 6.6 presents results from simulations with varying proportions of noisy recommender in the trader population. Simulations with 0%–50% of noisy recommenders were considered. The allocative efficiency of the system was significantly higher for all simulations where the subjective approach was used, therefore Hypothesis 6.3 is accepted. Rather interestingly, allocative efficiency is maintained even when 50% of the traders are providing random opinions, with the subjective reputation approach in use. Without the support of the subjective

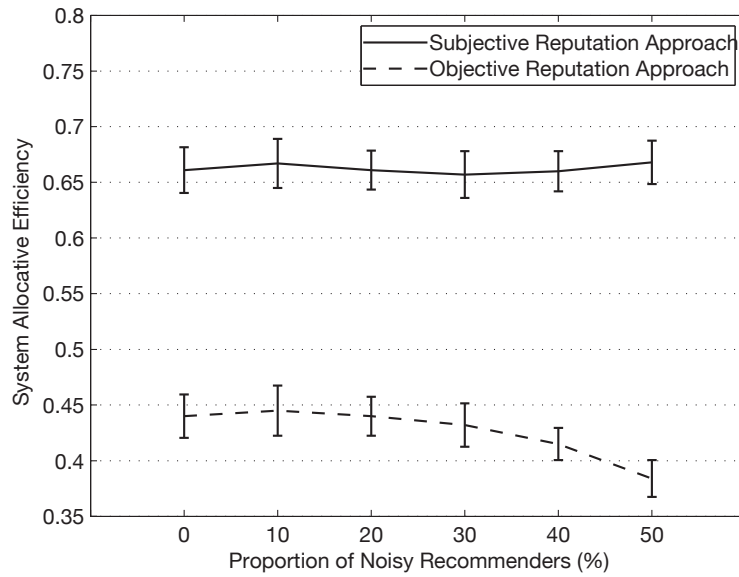


Figure 6.6: Mean system allocative efficiency for simulations involving varying levels of *noisy recommenders* in the trader population. A subjective reputation approach is quite resilient to very high levels of noisy recommenders, and accurate market-selection signals are still available even when 50% of the population is providing random opinions. By observing the results for 0% noisy recommenders it is possible to accept Hypothesis 6.2.

reputation approach, noisy recommenders certainly have a harmful impact in the system, as seen by a reduction in allocative efficiency for proportions of 30% or more. Figure 6.7 shows the *incremental* change in allocative efficiency as the proportion of noisy recommenders is increased. Again, efficiency loss gets *worse* in the objective reputation case, as the proportion of noisy recommenders decreases. Clearly, the subjective reputation system is performing very well, in terms of allowing traders to ignore noisy recommenders. Finally in this section, trader *recommendation connection* dynamics are analysed. Recall that if  $a_i$ 's recommendation weight  $\hat{\gamma}_{a_i, a_j}$  of  $a_j$  is in excess threshold  $\hat{\gamma}_{a_i}^* = 0.65$ ,  $a_i$  uses  $a_j$ 's opinion in reputation calculation, otherwise it is ignored. The following definitions, using the *constraint-induced niches* trader context notation introduced

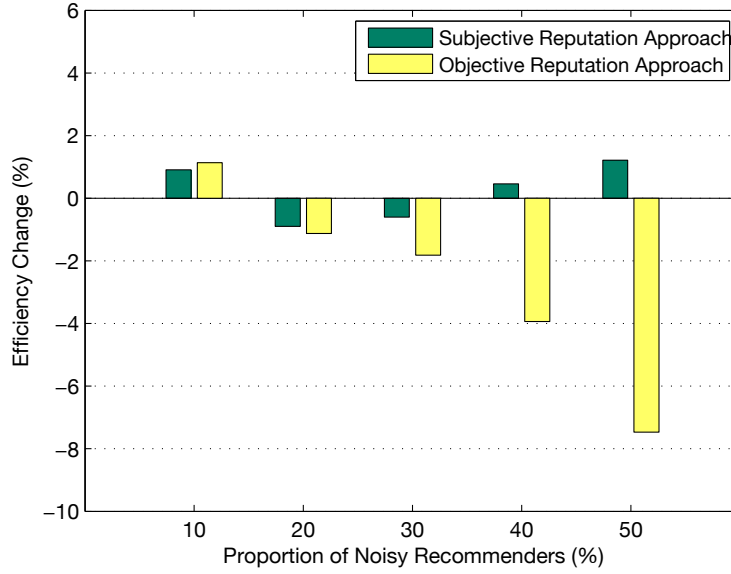


Figure 6.7: Incremental change in allocative efficiency experiments with increasing proportions of noisy recommenders. Not only does an objective reputation approach result in reduced efficiency as noisy recommenders increase, but the change in efficiency gets *worse* as the proportion of noise recommenders increases. Providing an explanation for some efficiency increases with noisy recommendations, e.g., from 0–10%, requires further investigation, but it is expected that it is increasing the *explorative* nature of traders, which may suggest that  $\varepsilon$  setting used for their reputation-based market-selection strategies may not be optimal.

in Section 5.3.1, are provided to help label different cohorts of traders:

$$B1 = \{a_i \in \mathcal{T} : a_i \in \mathcal{B} \cap \mathcal{T}_1^{Cl}\}$$

$$B2 = \{a_i \in \mathcal{T} : a_i \in \mathcal{B} \cap \mathcal{T}_2^{Cl}\}$$

$$S1 = \{a_i \in \mathcal{T} : a_i \in \mathcal{S} \cap \mathcal{T}_1^{Cl}\}$$

$$S2 = \{a_i \in \mathcal{T} : a_i \in \mathcal{S} \cap \mathcal{T}_2^{Cl}\}$$

Due to constraints in the *constraint-induced niches* trader context, B1 and B2 buyers prefer to trade in the same markets as S1 and S2 traders respectively. Thus, to a trader  $a_i \in B1$ , for example, the opinions of a trader  $a_j \in B2 \cup S2$  are not going to be helpful, because they are interested in different market niches.

Figure 6.8 visualises the mean frequency of recommendation weights  $\hat{\gamma}_{a_i, a_j} \geq \hat{\gamma}_{a_i}^*$  (considered maintained *recommendation connections*) between different cohorts of

6.5. AN EMPIRICAL ANALYSIS OF REPUTATION APPROACHES

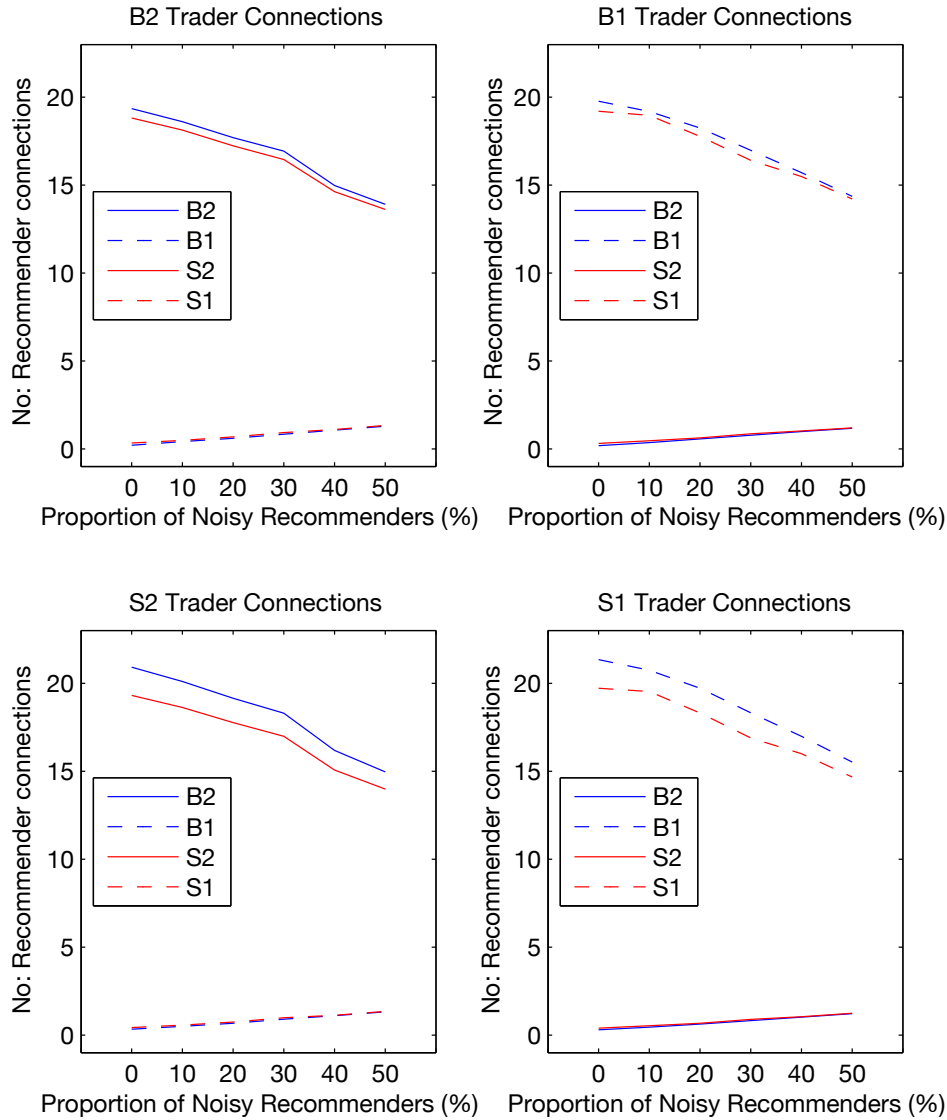


Figure 6.8: Mean frequency of recommender connections maintained between different *cohorts* of traders. Cohorts are identified as follows. ‘B’ refers to buyer and ‘S’ to seller, traders. ‘1’ and ‘2’ refer to different preference and constraint settings. Traders in this trader context prefer to trade one of two types of resource, thus there are two market niches in the environment, which market-exchanges will try to find. ‘B1’ and ‘S1’ traders would prefer a separate market to ‘B2’ and ‘S2’ traders. Therefore, opinions from traders in ‘1’ cohorts will not be helpful to traders in ‘2’ cohorts, and if traders’ recommendation weights for other decrease below the confidence threshold they will ignore the associated traders’ opinions. Firstly, the subjective approach enables traders to only maintain recommendation connections (and thus consider opinions) to traders that are helpful. Secondly, as the proportion of noisy traders increases, traders ignore their opinions, as evidenced by a general reduction in connections. One side effect of noisy recommenders is that due to their random recommendations, a small proportion of otherwise useless recommenders in fact provide (by chance) useful recommendations. This is seen in the small increase in some connection frequencies.

traders using the subjective reputation approach. There are two interesting observations: (i) traders maintain more recommendation connections to traders whose opinions are helpful to them, i.e, are interested in the same markets; and (ii) less recommendation connections are maintained as the proportion of noisy recommenders increases. This suggests that not only does the subjective approach enable traders to identify noisy recommenders and ignore them, but it also appears to enable traders to identify and consider opinions from traders who are interested in the same markets.

### 6.5.3 Dealing with lying recommenders

The empirical comparison between objective and subjective reputation approaches is continued in this set of experiments by assessing the impact of *lying recommenders*. The main research question to answer in this section is:

*What impact do increasing levels of lying recommenders have on resource allocations when objective and subjective reputation approaches are utilised?*

Based upon the success of the previous experiments an intuitive hypothesis would be:

**Hypothesis 6.4.** *In the presence of lying recommenders, resource allocations will always be more efficient when market-selection signals are formed using a subjective approach, because it enables traders to identify lying recommenders and ignore their opinions.*

An experimental setup identical to the last set of experiments is used, with the exception that lying recommenders are used instead of noisy recommenders.

#### Experimental Results

Each simulation was repeated 50 times, and mean results are reported. Again, experimental variations with increasing numbers of lying recommenders are carried out, as shown in Figure 6.9. In a similar fashion to the experiments

## 6.5. AN EMPIRICAL ANALYSIS OF REPUTATION APPROACHES

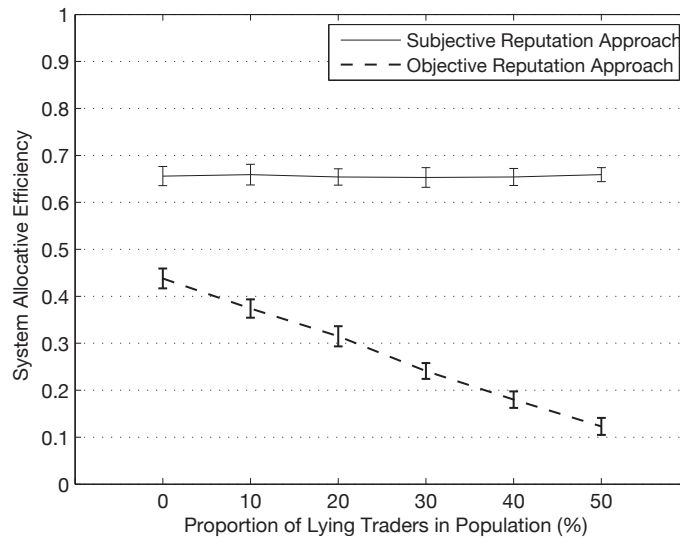


Figure 6.9: Mean allocative efficiency for simulations involving various levels of lying recommenders that are using the *Supply and Demand Attack*. Lying recommenders, because of their strategic information manipulation, are very damaging to the overall system efficiency, when, in the objective reputation approach, their opinions are considered equally to others. Lying recommenders specifically try to disrupt market equilibria to increase their own profits, which leads to inefficient allocations. Traders using the subjective reputation approach, however, are able to ignore the opinions of traders using this attack, resulting in the maintenance of high allocative efficiencies even when 50% of the opinions in the system are lies.

involving noisy recommenders, we find that the even with half of the trader population attempting to subvert the reputation of some market-exchanges, allocative efficiency is maintained only when the subjective reputation system is in use. Of particular interest is that the impact of lying recommenders is far more detrimental to the system than noisy recommenders, yet the subjective reputation approach still performs equally well. Thus, Hypothesis 6.4 is also accepted.

Figure 6.10 clearly shows that as the proportion of Lying Recommenders is increased, the change in system allocative efficiency is minimal, while when the objective reputation approach is used, efficiencies get progressively worse as the proportion of liars increases. Finally, a recommender connection analysis is performed and visualised in Figure 6.11. In contrast to the noisy recommender simulations (Figure 6.8), only certain cohorts of traders have their connections reduced as the number of liars using the *Supply and Demand Attack* increases.



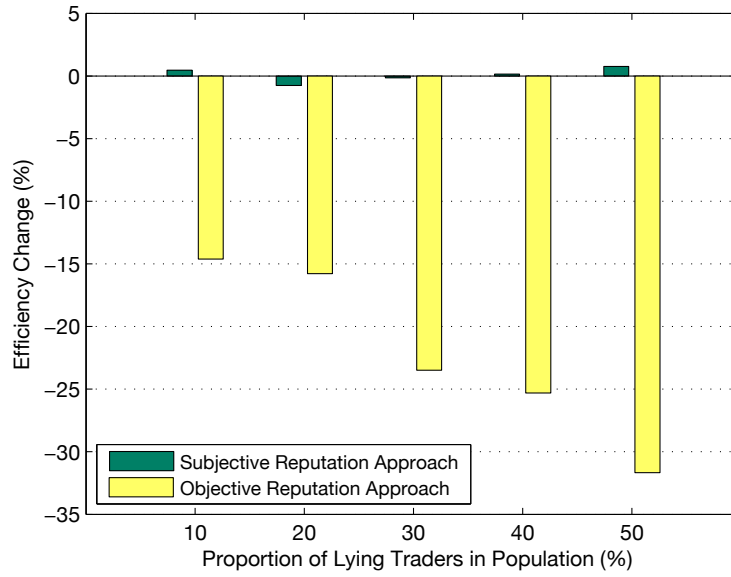


Figure 6.10: As with the experiments looking at the proportion of noisy recommenders, in this set of experiments the use of an objective reputation system results in the incremental change in allocative efficiency getting *worse* as the proportion of lying traders increases.

Thus, lying traders will only have their opinions ignored by a section of the population, because they still provide truthful opinions to other sections. This is a useful property in these types of market-based system where opinions may be both helpful and unhelpful to different traders.

#### 6.5.4 Recommender Network analysis

This section analyses some of the topological properties of the *recommender networks* that emerge within the system. A recommender network is a directed graph containing all the trader in the system, where an edge from trader  $a_i$  to trader  $a_j$  indicates that  $a_i$  uses  $a_j$ 's opinion when forming reputations of market-exchanges. Formally, given a recommender network graph  $G(\mathcal{T}, E)$ , where  $\mathcal{T}$  is the set of all traders and  $E \subset \mathcal{T} \times \mathcal{T}$  is the set of directed edges between traders, in the form of ordered pairs  $(a_i, a_j)$ , which satisfy:

$$\hat{\gamma}_{a_i, a_j} \geq \hat{\gamma}_{a_i}^* \iff (a_i, a_j) \in E, \quad (6.23)$$

6.5. AN EMPIRICAL ANALYSIS OF REPUTATION APPROACHES

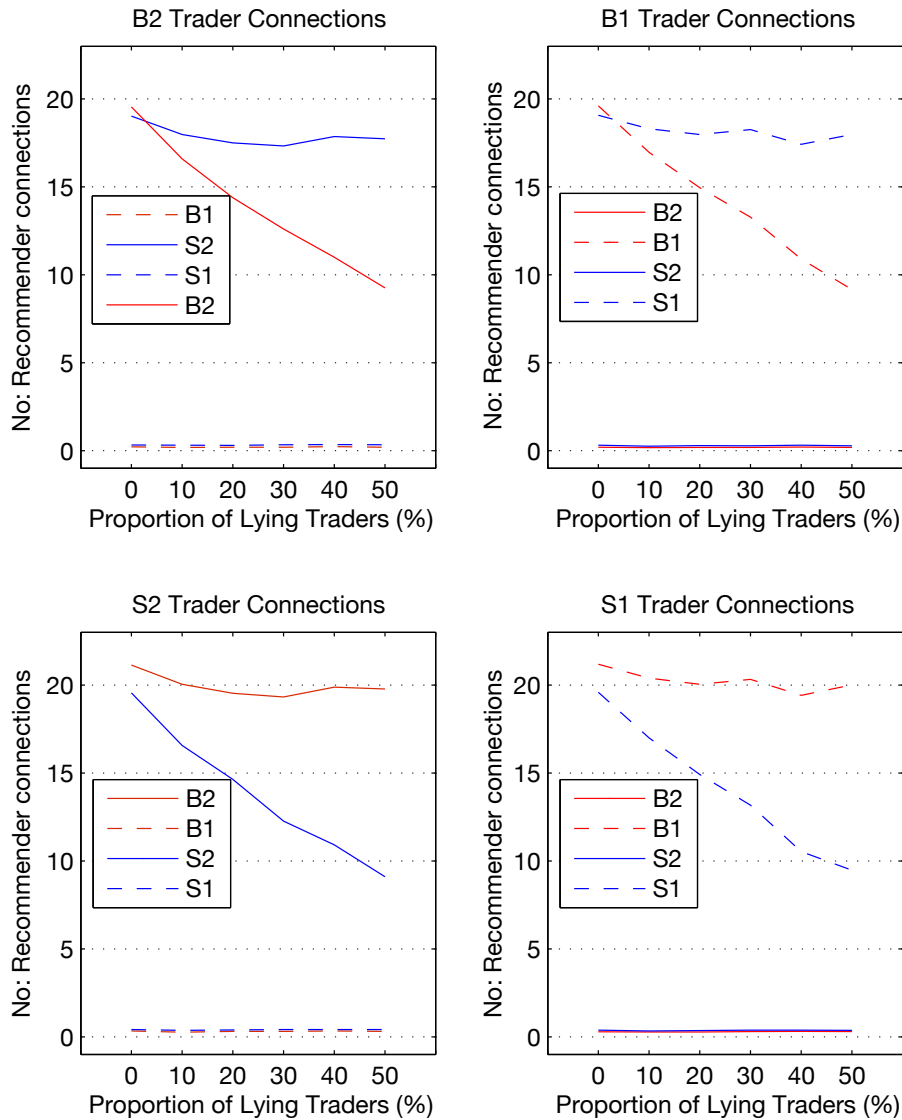


Figure 6.11: Mean frequency of recommender connections maintained between different cohorts of traders in simulations where there are varying proportions of lying recommenders. For explanations of the cohort labels and associated types see Figure 6.8 and Section 6.5.2. An increase in lying recommender proportions results in traders reducing the number of recommender connections it maintains to its *own type*. This is because lying recommenders only lie to traders who they are in competition with. For example, in the top left figure ‘B2’ traders ignore more ‘B2’ traders as the proportion of liars increase (top left), but the recommendation frequencies of helpful traders, e.g., ‘S2’ traders (that may also be liars), are not significantly effected. Therefore, the subjective reputation approach allows traders to ignore or include selected types of traders when forming reputations, even if those traders’ opinions are helpful or unhelpful to other traders.

where  $\hat{\gamma}_{a_i, a_j}$  is the recommendation weight  $a_i$  holds for  $a_j$  and  $\hat{\gamma}_{a_i}^*$  is  $a_i$ 's confidence threshold for including other traders' opinions. The recommendation weight learning process that occurs when agents are using the subjective reputation approach is particularly interesting, and understanding more about the resulting recommendation networks may help take a step towards the better design of reputation approaches for multi-attribute resource allocation systems. The overarching research question within this section is:

*What kinds of topological properties do recommender networks, emerging as a result of trader learning processes, possess?*

As well as wishing to visualise the recommender networks in order to qualitatively analyse some of the topological properties, a statistical quantitative analysis of the *recommender hierarchy* is carried out. In many real-world marketplaces and social hubs there exist influential entities that *coordinate*—intentionally or not—the decisions of other entities in the system, by facilitating *consensus* between other system participants. Examples of these influencers might include *newspaper critics*, *financial advisors*, or *prominent academics*. These types of networks can be useful in distributed systems, particularly if consensus and coordination are desirable properties. Such properties are certainly useful for the model studied within this thesis, because it can encourage the self-organisation of traders into markets that satisfy their market niche, leading to more efficient resource allocations. Of particular interest is whether the recommendation weight learning process within the subjective reputation approach results in the emergence of *influential traders* that might provide useful opinions to many traders, thus imposing consensus on market-selection.

There are many ways to measure how influential a trader is. Graph theorists, for example, might look at the *centrality* [16] of the trader in the recommender network, but given our recommendation network is weighted, that analysis doesn't capture the notion of influence very well. Rather, by asking each

## 6.5. AN EMPIRICAL ANALYSIS OF REPUTATION APPROACHES

trader for *their* favoured recommenders, e.g., their *top three* by recommendation weight strength, and then building a new *Favourite Recommender* graph, based on that information from all traders, a more meaningful analysis can be performed.

**Definition 6.1. (Favourite Recommender Graph):** is a subgraph  $\widehat{G}^k(\mathcal{T}, E^k)$  of the recommendation network graph  $G(\mathcal{T}, E)$ , where the Favourite Recommender Graph edge set  $E^k$  contains for each  $a_i$  at most  $k$  ordered pairs of edges  $(a_i, a_j) \in E^k$ . In the case that  $a_i$  has *more* than  $k$  edges  $(a_i, a_j)$  in the recommendation network graph edge set  $E$ , the  $k$  edges  $(a_i, a_j) \in E$  with the largest  $\widehat{\gamma}_{a_i, a_j}$  values are put into  $E^k$ , subject to  $\widehat{\gamma}_{a_i, a_j} \geq \widehat{\gamma}_{a_i}^*$ .

Therefore, based on Definition 6.1, the Favourite Recommender Graph will be a subgraph of the recommender network graph where for each trader vertex  $a_i \in \mathcal{T}$ , the trader's strongest  $k$  recommendation weights to other traders are represented as directed outgoing edges  $(a_i, a_j)$ . If  $k = |\mathcal{T}| - 1$  then  $\widehat{G}^k(\mathcal{T}, E^k) \equiv G(\mathcal{T}, E)$ , while in the case that  $k = 1$ , each trader in the graph has at most one outgoing edge to the trader whose opinions they find most helpful. Given an ordered pair  $(a_i, a_j) \in E^k$ ,  $a_j$  is defined as a *favoured recommender* of  $a_i$ .

Measuring the number of incoming edges that each trader has (its *in-degree*) in a Favoured Recommender Graph, it is possible to build an *in-degree frequency distribution*, and reveal the proportion of traders that are generally favoured *more* than others (and thus have a high in-degree). However, in many topologies it is common for some vertices to have more edges than others, even when randomly generated. To know whether an underlying mechanism is responsible for the in-degree distribution of the Favourite Recommender Graph (rather than it being a random artefact), one can *compare* a Favourite Recommender Graph frequency distribution to one that is *randomly generated* using the *same* recommender network supergraph.

**Definition 6.2. Random Recommender Graph:** A Random Recommender Graph  $\widetilde{G}^k(\mathcal{T}, E^k)$  is a subgraph of a recommender network graph  $G(\mathcal{T}, E)$ . It is formed in almost exactly the same way as the Favourite Recommender Graph  $\widehat{G}^k(\mathcal{T}, E^k)$  in Definition 6.1, with following difference: rather than selecting the top  $k$

ordered pairs  $(a_i, a_j)$  according to  $a_i$ 's recommendation weight for each  $a_j$ , for each  $a_i$ ,  $k$  pairs are randomly chosen from the set of pairs  $(a_i, a_j) \in E$ , subject to  $\hat{\gamma}_{a_i, a_j} \geq \hat{\gamma}_{a_i}^*$ . Thus,  $\tilde{G}^k(\mathcal{T}, E^k)$  is a *random* subgraph of  $G(\mathcal{T}, E)$ , where each trader  $a_i$  has at most  $k$  outgoing edges.

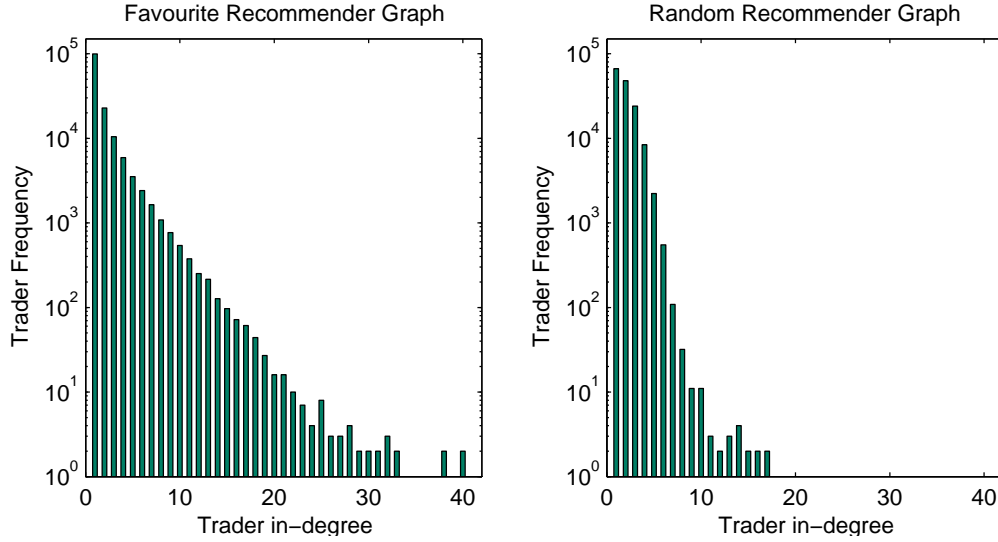


Figure 6.12: *In-degree* frequency density functions for the *Favourite Recommender Graph* and the *Random Recommender Graph*, built from a recommendation network graph taken from a typical simulation. The *Favourite Recommender Graph* has a *longer tail*, indicating that *most* traders are not considered *favoured recommenders* by any other traders (left side of distribution), but a few traders are considered *favoured recommenders* by many traders (right side of distribution). Therefore, a few traders within the system are very *influential*. Because the *Random Recommender Graph* is randomly generated from the same supergraph, and the distributions are statistically distinct, it is argued that a non-random process is responsible for the emergence of these *influential* traders.

In Figure 6.12, the in-degree frequency distributions for a *Favourite Recommender Graph* from a typical simulation, is calculated and plotted, where  $k = 3$ . Firstly, many traders have an in-degree of zero, indicating that most traders are not considered *favoured recommenders* by others, however a few traders have very high in-degrees, indicating that in some cases up to 40 traders (13% of the population) consider them as one of their *favoured recommenders*.

The Kolmogorov–Smirnov<sup>2</sup> (KS) test non-parametrically tests the null hypothesis

<sup>2</sup>The K-S test assumes that a continuous empirical CDF [155] is provided, as this allows the KS statistic to converge to a well behaved distribution, as the sample size approaches infinity; thus the KS test in the discrete case is an approximation.

that the frequency of events observed in two independent samples are consistent with each other, i.e., arise from the same distribution. Williams [181] provides several arguments as to why the Kolmogorov–Smirnov test may be more accurate than the more commonly used *Pearson’s Chi-Squared Test* [131], which also only allows one to compare against a theoretical distribution. Performing the KS test on the two distributions shown in Figure 6.12 reveals that the null hypothesis—the samples are from the same distribution—can be rejected, and thus they are statistically distinct distributions. The reported  $p\text{-value} < 0.005$ , and the  $KS\ test\ statistic = 0.2179$ ; the two samples were made up of 350,000 observations each. This suggests that the subjective reputation system is capable of allowing these types of hierarchies to emerge.

### Visualising Recommender Networks

This section provides the reader with some visualisations of *recommender networks* from typical simulations. To do this, the Java Universal Network and Graph Framework [122] was integrated into the simulation framework, which allows traders to be visualised as vertices and recommendation weights as edges. There were several initial motivations for analysing the networks in this way: (i) it is not clear from only performing in-degree and out-degree frequency analysis, *who* traders connect to; and (ii) what impact do trader preferences and constraints or profitability have on the connections they maintain? The network visualisations are typical of a simulation that contains either 300 constraint-based, or preference-based traders. Each trader  $a_i$  can have many out-going recommendation weights  $\hat{\gamma}_{a_i, a_j}$  to other traders  $a_j \in \mathcal{T}$  that satisfy  $\hat{\gamma}_{a_i, a_j} \geq \hat{\gamma}_{a_i}^*$ . However, *visualising* all of these connections leads to a very *dense* graph, which is hard to analyse, so instead the *Favourite Recommender Graph* is visualised where  $k = 3$ . The following visualisations provide support to the previous result, namely: most traders have a low in-degree, while a few have a high in-degree. Further, they provide evidence to show the *self-organising* properties of the

subjective-reputation approach. Figure 6.13 visualises a *Favourite Recommender*

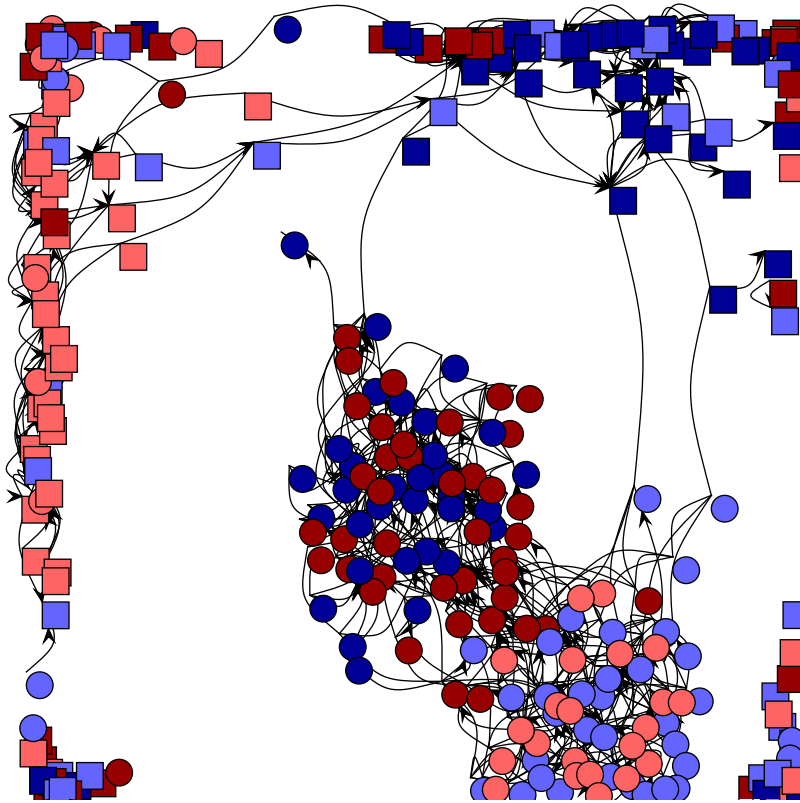


Figure 6.13: A visualisation of a typical Favoured Recommender Graph from a simulation using a *constraint-induced niches* trader context, at a single point in time. Different shades indicate traders that belong to different market segments and thus prefer to trade in different markets, i.e., darkly (lightly) shaded traders in general find the opinions from other darkly (lightly) shaded traders helpful. Buyers are coloured *blue* and sellers *red*. *Extra-marginal* traders—those who have recently failed to successfully trade—are drawn with a *square*, while *intra-marginal*—those who have recently traded—traders are drawn with a *circle*. Edges between traders are directed such that an *out-going* edge from trader  $a_i$  to  $a_j$  means that  $a_i$  uses the opinions of  $a_j$  to form reputations of market-exchanges, i.e.,  $\hat{\gamma}_{a_i, a_j} \geq \hat{\gamma}_{a_i}^*$ . A *force-based* algorithm [60] is used to position the traders within the space. Traders can have at most  $k = 3$  outgoing edges, but potentially up to  $|\mathcal{T}| - 1$  incoming edges. The more incoming and outgoing connections a vertex has, the more centrally it is positioned.

*Graph* from a snapshot of a simulation containing multiple niches, and thus traders who prefer different market segments. Notice several observations:

1. Traders with similar resource preferences, i.e., prefer the same market niche, are generally highly connected;

## 6.6. CONCLUSIONS AND DISCUSSION

2. *Extra-marginal* traders don't share many connections with *intra-marginal* traders, but they do tend to share connections with *each other*. This suggests that if—due to an exchange selecting a new resource type—a better market becomes available, they can quickly share that information with each other;
3. *Extra-marginal* traders also tend to be more connected to all trader types (indicated by dark and lighter shades connecting). This may facilitate the quick spreading of information regarding the previous point.

Finally, the reader may notice a reasonable amount of connectivity between *some* intra-marginal dark red sellers, and traders of other types, i.e, lightly coloured. This is because traders that are dark can provide all resource types (they have no minimum attribute-level constraints) to any buyer, thus they share opinions on market-selection. Figure 6.14 visualises a Favourite Recommender Graph of a simulation containing traders from the *preference-induced niches* trader context. Because these traders don't have constraints (only preferences over attributes), there are *fewer* extra-marginal traders (traders can trade resources with any attribute-levels). Due to the lower extra-marginal traders, more traders tend to connect together, as there is less chance an opinion results in a trader not trading—thus all opinions are generally more helpful.

## 6.6 Conclusions and Discussion

Prior to this chapter, trading agents only considered their own private information when making market-selection decisions, which was an expensive initial process when entering the system involving having to always directly join markets to evaluate their suitability. This chapter considered, for the first time, the application of a subjective reputation approach, grounded in Bayesian statistics, to the problem of facilitating market-selection in the novel multi-attribute model of resource allocation studied throughout this thesis. Inline with real-world open and dynamic multi-agent systems, this chapter considers an extension to the multi-attribute market-based model, by assuming *trader churn* exists within the model, which is defined as different traders joining and leaving at different times.



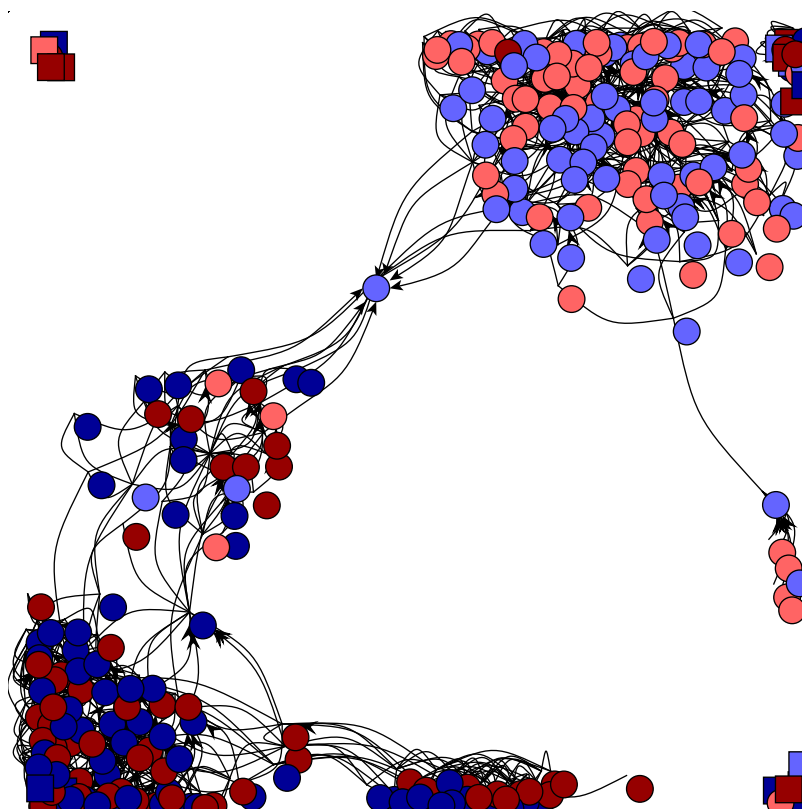


Figure 6.14: A visualisation of a typical Favoured Recommender Graph from a simulation using a *preference-induced niches* trader context, at a single point in time. In the *preference-induces niches* trader context, there are two market niches. Therefore, there are again dark and lightly shaded traders. Buyers that prefer the first resource attribute, and sellers that can provide the first attribute at less cost, are lightly shaded. While those who prefer and can supply more cheaply, the second attribute, are darkly shaded. While one trader appears to be heavily linked to both types of trader in the population, situations such as this tend to appear and disappear quite often when viewing simulations, presenting some interesting future work to more closely analyse the dynamics of the recommender networks. All other details are explained in Figure 6.13.

While other subjective Bayesian approaches [166, 165, 97] have considered both noisy and manipulative information, the domains they consider are different to the market-based model in this chapter, and it is unclear of the effectiveness of these approaches in multi-attribute resource allocation models. This chapter made progress in this direction by designing two new behaviour models: *Noisy Recommenders*, which are designed to mimic potentially faulty software agents, and *Lying Recommenders*, which using the *Supply and Demand Attack*, are engineered to specifically manipulate the reputation system such that it directly

## 6.6. CONCLUSIONS AND DISCUSSION

improves their profit margins.

Using these, as well as a variety of market conditions, this chapter empirically analyses both the impact that churn has on the efficiency of resource allocations, and impact that a subjective reputation approach has on efficiency. Results demonstrated that in the absence of reputation, system churn reduces the allocative efficiency of the system dramatically as it increases, while when traders use reputation information this loss is significantly reduced. Further, results also demonstrated that the subjective reputation approaches were also able to deal with the presence of significant proportions of noisy and lying recommenders without any measurable loss to system efficiency.

Therefore, the contributions of this chapter are:

- The proposal and application of a subjective reputation approach to tackle the problem of market-selection in a market-based environment containing multiple competing marketplaces;
- Models of two types of trader behaviour expected within a multi-attribute market-based model: *Noisy Recommenders*, and *Lying Recommenders*, who attempt to strategically manipulate reputation information to alter supply and demand in a two-sided market;
- Experimental evidence showing not only that reputation information improves market-selection signals under dynamic scenarios, leading to more efficient resource allocations, but that a subjective reputation approach allows traders to maintain connections to helpful recommenders and ignores harmful or inaccurate ones;
- An initial analysis of the properties of emergent recommender networks, using visualisation techniques and a novel statistical graph reduction approach to measure the influential properties of traders using the subjective reputation approach.

This chapter does not claim that the reputation approach used is necessarily the best, and as such does not compare performance of different reputation systems. The main aim of the chapter was to see what impact reputation, in terms of publicly shared market-selection decisions, had on the outcomes of the system. While previous work has already shown subjective reputation approaches can work well in the presence of malicious or false information, this chapter has advanced the state-of-the-art by showing that subjective reputation information can also be very important in market-based systems for allowing cohorts of traders to signal to each other which markets they should all join, thus improving market segmentation, and the efficiency of allocations.

Statistical analysis of typical recommender networks found that while a large proportion of traders were no-ones' favoured recommenders, a few were highly favoured by many. This leads to frequency distributions that are remarkably similar (though not identical) to *Pareto* distributed networks [171], and large interconnected networks similar to those found in other studies of social networks used for spreading gossip or opinions [190]. Because these approaches appear to lead to highly influential groups of traders, which encourages cohesive decisions within the population, future work should look at any negative effects this process may cause. For example, phenomena such as *Groupthink* [75], where a tightly-knit group of individuals fail to effectively examine all alternatives in favour having a consensus view, might actually lead to sub-optimal market-selection in some cases. Further, weighted recommendation networks of type studied in this chapter might encourage a type of *disconfirmation bias* [50], where conflicting traders are overwhelmed by third-party information supporting one view when they are a small group may have conflicting information. Further work will explore these phenomena further, overall focussing on the design of more effective and robust reputation approaches for trader market-selection.

## CHAPTER 7

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# CONCLUSIONS

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This thesis has studied a novel approach for allocating multi-attribute computational resources in distributed, dynamic and open environments. The approach considers multiple competing marketplaces offering double auction markets for specific types of computational resources, while resource consumers and providers, using decision-making behaviours inspired by marketing models grounded in consumer theory, choose between markets according to whichever best satisfies their preferences and constraints. The approach satisfies a number of properties desirable in distributed utility computing environments (see Section 2.1.3). Specifically, the approach is:

- *robust*: because it does not rely on a single centralised co-ordinator or mechanism;
- *scalable*: because more marketplaces can be added without the need to coordinate or communicate with any existing ones;
- *expedient and available*: because it uses a continuous mechanism to allocate resources between traders as soon as two matching traders submit matching offers;
- *open*: because traders do not need to have complex bidding or bargaining strategies, and the public nature of marketplaces means all trader have equal access to prices within a market.

While approaches to single-attribute resource allocation via competing marketplaces have been considered within the literature before, effectively allocating multi-attribute resources in a similar way required tackling several challenges, as well as developing a new market-based model. In Chapter 4, a model of multi-attribute resource allocation via competing marketplaces was formally described, and mechanisms describing agent behaviour developed, as well as an algorithm for measuring the efficiency of the market-based system during simulation.

Chapter 5 considered the *automatic niching problem*, which exists because it is desirable that market-exchanges are able to *autonomously* locate and compete over the market niches that most satisfy segments of the trader population; this

particularly challenging due to the multiple learning processes occurring in the environment. Approaches for tackling this challenge, using *attribute-level selection* (ALS) strategies were proposed and analysed, and results suggested that under a variety of conditions, market-exchanges were able to locate the market niche(s) that most satisfied various market segments, leading to efficient outcomes. Further to this, the novel methodology developed in Chapter 3 for quantitatively and qualitatively assessing the generalisation properties of market mechanisms, was applied to the study of ALS strategy performance. Results of a comprehensive computational study revealed that although no ALS strategy was robust against all environmental conditions, a number of environmental factors that affected ALS strategy performance were discovered, hopefully taking a step towards designing more robust strategies in the future.

Finally, Chapter 6 considered a more dynamic extension to the model, in which traders continually leave the system, while new ones join, as might be expected in a real-world distributed and open setting. Under such conditions the dynamic nature of marketplaces makes learning accurate market-selection signals potentially expensive for new traders. Chapter 6 considered the application of a Bayesian statistics reputation approach to the problem of facilitating traders' market-selection decisions, and demonstrated that subjective reputation-based market-selection strategies lead to more efficient resource allocations in a variety of dynamic environmental settings. As well as subjective reputation information—where traders value different traders' opinions differently—enabling traders to ignore spurious opinions within the system, the information also enabled them to identify influential traders. This leads to more consensual market selection by traders in general, resulting in higher volume and more liquid markets, leading to more efficient resource allocations.

## 7.1 Summary of Thesis Contributions

In summary, this thesis has made the following main contributions:

- A novel methodology for measuring the generalisation properties of competing market mechanisms in coevolutionary trading environments. The methodology was applied to market mechanisms submitted to TAC Market Design Competitions, and showed that a number of these mechanisms did not generalise across environmental situations, demonstrating the methodology's appropriateness.
- A novel approach for allocating distributed multi-attribute computational resources, using multiple competing marketplaces, which each satisfy market segments by running markets for specific types of computational resource.
- The formulation of decision-making models for traders, which allows them to value multi-attribute computational resources, and reason over marketplaces offering these, using marketing models grounded in consumer theory.
- An algorithm for calculating the optimal allocation of multi-attribute computational resources between traders with different preferences and constraints over resource attributes, using combinatorial optimisation methods.
- The first clear formulation of the *automatic niching problem*, which presents itself when marketplaces must decide what type of resource market to offer to traders with unknown and diverse resource preferences and constraints, and within an environment with competing marketplaces attempting to do the same.

## 7.1. SUMMARY OF THESIS CONTRIBUTIONS

- A thorough empirical analysis of the effectiveness of *n-armed bandit* and *evolutionary optimisation* market niching strategies for tackling the automatic niching problem, within a variety of representative environmental situations.
- The first application of a reputation-based approach for facilitating selection between double-auction marketplaces by integrating reputation information into market-selection strategies.
- An analysis of the performance of reputation-based approaches to market-selection, demonstrating that subjective reputation information improves market-selection decisions, which leads to more efficient allocations globally.

In terms of market-based approaches to multi-attribute resource allocation, the approach advocated and studied within this thesis sits—with purposeful pragmatism—somewhere between fully decentralised and fully centralised models of resource allocation. Allocating multi-attribute computational resources via multiple competing marketplaces creates a distributed market-based environment, where traders are free to migrate between various institutional exchanges, and thus do not rely upon any single mechanism. Further, allocations are often very efficient because: (i) traders are aware of market prices and, when a reputation approach is used, aware of the most profitable markets, thus no individual trader is at a disadvantage; and (ii) market-exchanges, using attribute-level selection-strategies, are in many cases able to locate the market niches that most satisfy traders' preferences and constraints. Therefore, the approach, and thus contributions within this thesis supporting the approach, are significant, because the approach represents a valid alternative to either fully decentralised (robust but economically inefficient) or fully centralised (economically efficient but computationally prohibitive and brittle), models of multi-attribute resource allocation. However, this thesis does not claim that this



approach is *generally better* than any other, only that it satisfies designer objectives, and therefore is *suitable*, for the application envisaged, viz., the allocation of distributed multi-attribute computational resources between self-interested software agents.

One of the underlying issues in this thesis was generalisation and robustness, particularly in terms of double auction market mechanisms competing in dynamic and open environments. The complexities of these *coevolutionary* systems preclude using theoretical approaches to design mechanisms that can generalise across all environments or situations. Thus, significant research effort focusses on empirical approaches to the design of more robust market mechanisms, which generalise well across environments. In that respect, contributions made within this thesis are significant for two reasons: (i) the mechanisms developed within this thesis are adaptive by design—in their absence the market-based system would be less robust against various environmental factors; and (ii) the methodology developed for empirically assessing the generalisation properties of market mechanisms can be used by others working in this research area, to guide the design of mechanisms that generalise better.

Finally, much of the work carried out within this thesis involves exploring aspects of competition between marketplaces. To that end, several techniques were developed for discovering not just mechanisms' sensitivities to competitors, but also for visualising the outcomes of complex interactions between competing market mechanisms. In that case, it is hoped that these methods and techniques will be useful for anybody that is interested in analysing competition between marketplaces, be it from a computer science, economics, or marketing, perspective.

## 7.2 Future Work

This thesis is a stepping stone towards the design of robust and efficient market-based approaches to computational resource allocation in large-scale distributed systems. Therefore, in this last section, some future work is outlined, by considering some of the limitations of the work described within this thesis.

This thesis did not claim that the approach studied was the best approach to tackling computational resource allocation problems, only that it was *suitable*. It is hard to directly compare this approach to others, such as fully decentralised or fully centralised approaches, because ‘*better*’ is multi-objective in nature, encompassing, for example: economic efficiency, scalability, and robustness. However, it would be interesting and important to directly compare this approach with others across the multiple objectives, so that other researchers or practitioners could better understand what approach would suit their needs best. To make this assessment, the methodology developed in Chapter 3 could be extended so that it considers performance within multiple dimensions, when assessing the generalisation properties of market mechanisms within different environments. Potentially, a researcher or practitioner could then better design mechanisms for the environments they are expected to operate in.

In terms of directly improving the market-based approach studied in this thesis, a significant next step would be to consider more generalised versions of the model, which would have properties closer to those expected within a real-world implementation. Specifically, the model presented in Chapter 4 is purposely simplified to ease analysis within this thesis. All resources modelled in this thesis had two non-price attributes, yet it is quite common for real-world computational resources to have more for example [2], so an important next step is to consider the impact of resources with higher numbers of attributes. Another simplifying step was to create very clear market segments, which aided the identification of well-defined market niches, in the form of resource types that

large proportions of the trader population clearly preferred. Increasing the number of resource attributes, and making market segments less clear, potentially has significant impacts on the performance of market-exchanges' attribute-level selection-strategies. While results suggested in Chapter 5 that *bandit* strategies significantly out-performed *evolutionary optimisation* approaches, as the dimensionality of the attribute-level space increases and the market segmentation in the trader population becomes less clear, it is less likely that bandit strategies' action sets will contain the resource types that most satisfy available market segments. In such a case, the attractiveness of *evolutionary optimisation* approaches, which can select *any* point in the resource-attribute space, increases. Indeed, Chapter 5 did not claim that n-armed bandit approaches were better than evolutionary optimisation approaches *in general*, only in the representative environments considered within the constraints of the model studied. It is possible, for example, that diversity techniques such as *fitness-sharing schemes* [149] will improve evolutionary ALS strategy performance in higher-dimensional resource-attribute spaces.

Finally, Chapter 6 considered using reputation only in a signalling role, but not in a *sanctioning* role. A very important extension to this work is to consider the potential issue of market failure that could occur if this model is situated within real-world open distributed systems. Market failure can occur in real-world markets when there is either adverse selection [1] or moral hazard [27]. And, because of the considerable distance among trading partners, both types of information asymmetry are possible [37, p. 31]. Real-world financial exchanges deal with moral hazard under the term *counterparty risk*, and they mitigate against it by demanding all market participants leave enough *margin* in their accounts—suitable funds for the exchange to reimburse any party that loses out in a transaction. Within this model, market-exchange reputation is even more important, because exchanges would be required to be trusted with participants' funds.

## 7.2. *FUTURE WORK*

Adverse selection behaviour might include sellers intentionally entering a market and providing resources that are not of the same type as those described. Two approaches for dealing with this include the use of a two-stage mechanism, such as [170], or, perhaps more preferably, allowing traders to factor in losses and incorrect resource provision into marketplace reputation. In that case, market-exchanges would be incentivised to actively monitor which types of seller are allowed into their markets, or perhaps incentivise good behaviour by charging fees according to seller performance. In general, this type of research begins to reach into many other areas, including computer security, economics, and network theory.



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## ☞ Colophon ☞

This dissertation was written on a Mac using the rather fabulous TextMate<sup>1</sup> editor, making regular use of both the  $\LaTeX$  and SVN bundles. The document was typeset using the  $X_{\LaTeX}$ <sup>2</sup> typesetting system, which is based on a merger of Donald Knuth's  $\TeX$  with Unicode and modern font technologies. The Linux Libertine<sup>3</sup> (Libertine Open Fonts Project) typeface is used to typeset all latin serif, and digit, characters within the document, while all math is typeset in Minion Pro (Adobe Systems); sans-serif characters are typeset in either Monaco (Apple) if monospaced, or Neue Helvetica (Linotype GmbH) otherwise.

All figures were plotted in Mathwork's MATLAB, version R2009b and outputted directly as PDF files; the *heat maps* presented in Chapter 5 were produced using the Pseudocolor surface plot function, with each point coloured according to a bilinear interpolation of the colours at its four vertices.

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<sup>1</sup><http://macromates.com/>

<sup>2</sup>[http://scripts.sil.org/cms/scripts/page.php?site\\_id=nrsi&id=xetex](http://scripts.sil.org/cms/scripts/page.php?site_id=nrsi&id=xetex)

<sup>3</sup><http://www.linuxlibertine.org/>



*Well, I don't, I don't really think that the end can be assessed. . . uh as of itself as being the end because what does the end feel like? It's like saying when you try to extrapolate the end of the universe you say if the universe is indeed infinite then how—what does that mean? How far is, is, is all the way and then if it stops what's stoppin' it and what's behind what's stoppin' it, so what's the end, you know, is my question to you. . .*

—This Is Spinal Tap (1984)