CREDIBILITY-BASED BINARY FEEDBACK MODEL FOR GRID RESOURCE PLANNING

by

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Grid service providers (GSPs), in commercial grids, improve their profitability by maintaining the least possible set of resources to meet client demand. Their goal is to maximize profits by optimizing resource planning. In order to achieve such goal, they require feedback from clients to estimate demand for their service. The objective of this research is to develop an approach to build a useful value profile for a collection of heterogeneous grid clients. For developing the approach, we use binary feedback as the theoretical framework to build the value profile, which can be used as a proxy for a demand function that represents client's willingness-to-pay for grid resources. However, clients may require incentives to provide feedback and deterrents from selfish behavior, such as misrepresenting their true preferences to obtain superior services at lower costs. To address this concern, we use credibility mechanisms to detect untruthful feedback and penalize insincere or biased clients. We also use game theory to study how the cooperation can emerge.

In this dissertation, we propose the use of credibility-based binary feedback to build value profiles, which GSPs can use to plan their resources economically. The use of value profiles aims to benefit both GSPs and clients, and helps to accelerate an adoption of commercial grids.

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PREFACE

I would never have been able to finish my dissertation without the excellent guidance of my advisor and committee members, the wonderful support from my parents and family, and the amazing friends during my stay in Pittsburgh.

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1. INTRODUCTION

Grid computing has been successful enabling the establishment of virtual computing resources in large research institutions. A number of information technology (IT) organizations have built initial commercial implementations to deliver high-capability services for their own purposes. IRC[1] forecasts that the grid-computing market will grow from $1.8 billion in 2006 to approximately $24.5 billion in 2011 [1]. However, grid computing is still in the early adoption phase for mainstream commercial computing. This chapter provides a brief background of grid computing technology and a motivation of this dissertation.

1.1. BACKGROUND

1.1.1. Grid Computing

Grid computing has emerged as a significant new model of large-scale computing. The Globus Alliance[2] defines grid computing as [2],

> "The grid refers to an infrastructure that enables the integrated, collaborative use of high-end computers, networks, databases, and scientific instruments owned and managed by multiple organizations. Grid applications often involve large amounts of data and/or computing and often require secure resource sharing across organizational boundaries, and are thus not easily handled by today's Internet and Web infrastructures."

[1] Insight Research Corp., market analysis report, Available: http://www.insight-corp.com/
[2] Globus Alliance, a research and development project, Available: http://globus.org/

Grid computing is a merging of communication networks and computing infrastructure that geographically coordinates distributed heterogeneous resources for solving large-scale problems. The main objective of grid computing is to significantly reduce the execution time of data processing jobs or file sharing jobs while making effective use of resources. Consequently, by utilizing excess computing resources spread around the world (from individuals, institutions, and organizations), large complex problems can be solved in a sensible amount of time[3] without the use of supercomputers.

The difference between non-grid (such as cluster) and grid computing is the way resources are managed. In the cluster case, resource allocation is performed by centralized resource management systems and resources are usually owned by a single organization [2]. On the other hand, in the case of grid computing, resources might be distributed across multiple domains and owned by different organizations. This increases complexities when designing grid resource management systems.

1.1.2. Grid System Taxonomy

In this section, we present grid system classification in term of its constructions and objectives. Weiss et al. [6, 11] present three different ways in which grids can be constructed: *voluntary, involuntary,* and *commercial (centrally formed) grid*. According to the resource allocation method of each grid model, construction costs of voluntary and involuntary grids are cheaper than commercial grids. However, system performance of voluntary and involuntary grids has high variance, which makes it difficult to predict. As a result, there is a tradeoff between cost and

[3] Given high-capacity grids (such as TeraGrid) that have a larger computing capacity than supercomputers, the total computing time for a large complex problem should be significantly decreased.

system performance. If the main concern is system performance, commercial grids might be a better choice than others because of their predictability.

According to Krauter et al. [7], grid models are constructed for three main objectives: computational grids, data grids, and service grids. *Computational grids* require a number of CPU cycles while *data grids* require a huge bandwidth. *Service grids* are hybrid, which require a large number of CPUs and significant bandwidth. A summary of grid system taxonomy is presented in Table 1.1-Table 1.2. In this dissertation, we mainly concentrate on commercial grid computing.

Table 1.1 Grid Model Description.

Model	*Cost*	*System Performance*	*Description*	*Some Current Projects*
Voluntary Grid	Medium-Low	Unpredictable	Participants donate their idle resources to grid projects. In non-profit project (altruistic grid), donors do not expect any reward. But, donors join non-altruistic grid because of tangible reward (monetary or non-monetary).	Altruistic grid: SETI@home[4], Folding@home[5], Evolution@home[6], and ChessBrain[7]. Non-altruistic grid: MoneyBee[8], GStock[9], and Gomez Peer[10].
Involuntary Grid (Private Grid)	Medium-Low	Unpredictable, but better than voluntary	Private grids harvest idle resources in their organizations to achieve their purposes.	N/A
Commercial Grid (Centrally Formed)	High	High	Grids are designed for a large-scale scientific research. They are supercomputer-like computing network.	TeraGrid[11], BIRN[12], PPDG[13], and GriPhyN[14]

[4] SETI@home, The Search for Extraterrestrial Intelligence. Available: http://setiathome.berkeley.edu/
[5] Folding@home distributed computing. Available: http://folding.stanford.edu/
[6] Evolution@home and evolutionary-research. Available: http://evolutionary-research.net/
[7] ChessBrain, the world's largest chess computer. Available: http://www.chessbrain.net/
[8] MoneyBee (non-monetary reward). Available: http://uk.moneybee.net/index.asp
[9] GStock (non-monetary reward). Available: http://www.gstock.com/
[10] Gomez Peer (monetary reward). Available: http://peer.gomez.com/aspx/ProgramDetails.aspx
[11] TeraGrid. Available: http://www.teragrid.org/
[12] BIRN, Biomedical Informatics Research Network. Available: http://www.nbirn.net/

Table 1.2 Grid Model Taxonomy.

Grid Type	*Description*	*Resource Requirement*
Computational Grid	Grids that have very high-aggregated-computational capacity to solve large-scale problems, such as weather modeling, nuclear simulation, and Monte Carlo simulation.	CPU-Intensive
Data Grid	Grids that provide an infrastructure for data storage and access, which are distributed over a wide area network (WAN), such as digital libraries or data warehouses.	Bandwidth-Intensive
Service Grid	Grids that provide on-demand, real-time collaborative, and real-time multimedia services.	CPU-Intensive, and Bandwidth-Intensive

1.1.3. Commercial Grid Environment

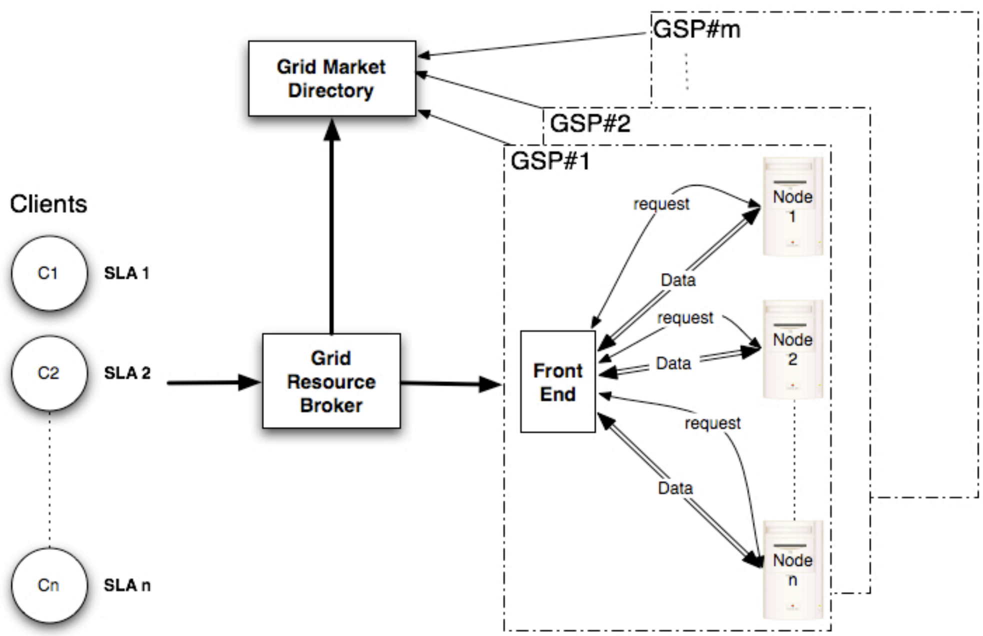

Figure 1.1 Typical commercial grid environment.

[13] PPDG, Particle Physics Data Grid. Available: http://www.ppdg.net/
[14] GriPhyN, Grid Physics Network. Available: http://www.griphyn.org/

Grid service providers (GSPs) and clients are the two key stakeholders in commercial grids. GSPs are agents who control resources and client are users of these resources. Figure 1.1 illustrates a typical commercial grid environment[15]. Many studies have modeled grid resource brokers and grid schedulers, for example AppLeS, Condor-G, and Nimrod-G. The summary of previous studies is provided in Buyya [8]. Thus, in this dissertation, we only concentrate on the interaction between clients and GSPs by ignoring the role of brokers. We assume that a client directly sends a job (request) based on his/her constraints (such as budget and preferred duration) to a GSP, who promises to provide a service to the client according to a service level agreement (SLA). The SLA is required to accomplish the goal agreed upon by both the client and the GSP. After the job is completed, the GSP returns the result to the client along with the service charge.

1.1.4. Costs of Computing

> *"The costs of computer systems increase at a rate equivalent to the square root of their power," stated by the Grosch's law [4, 38].*

Computing costs are not free. Most people think that computing costs of voluntary grids are free since participants donate their idle resources to grid projects. To understand the costs of these systems, we sent survey questions to several distributed computing projects. Unfortunately, we heard back from only four projects, as summarized in Table 1.3. The costs consist of hardware cost, software cost, bandwidth cost, and operation cost. Clearly, SETI@home has operation cost that far exceed other costs while Folding@home has a big investment in hardware part.

[15] Grid resource broker is an agent who finds GSPs for clients while Grid market directory contains a list of all GSPs in a market.

Involuntary and commercial grids are usually funded by sponsors. For example, between 2001 and 2005 the NSF[16] has supported the TeraGrid project with $240 million. As of early 2006, all TeraGrid resources provide more than 102 teraflops[17] (TFLOPs) of computing capability and more than 15 petabytes of data storage with fast access and retrieval over high-speed networks [5].

Table 1.3 Cost Survey of Distributed Computing Projects on Dec. 2005.

Cost	*Distributed Computing Project*			
	SETI@home	*Folding@home*	*Evolution@home*	*ChessBrain*
Server	$30,000	$150,000	$2,000	$30,000
Database	$10,000	$10,000	$300	N/A
Software	$1,000/year	$0	$300	$0
Bandwidth	$1000/month	Paid by Stanford University[18]	Paid by University of Edinburgh[19]	Donated by BTEG network[20]
Network device	$5,000	$4,000	N/A	Donated
Operation	$350,000/year	$50,000/year	N/A	Donated
Capacity (TFLOPs)	149.8[21]	200[22]	N/A	N/A

1.2. MOTIVATION

GSPs, in commercial grids, improve their profitability by maintaining the least possible set of resources to meet client demand [16]. GSPs can increase their profits by either increasing their

[16] National Science Foundation (NSF). Available: http://www.nsf.gov/
[17] FLOPs (Floating point Operations Per Second) is used as a measure of a computer's performance, especially in fields of scientific calculations.
[18] Folding@home project is supported by Stanford University.
[19] Evolution@home project is supported by University of Edinburgh.
[20] BTEG Networks host the ChessBrain project using their spare bandwidth.
[21] Anderson and Fedak [37] present the approach to estimate total processing capacity of SETI@home project. The result indicates that SETI@home had a processing rate of 149.8 TFLOPs, as of May 2006.
[22] Folding@home has 200,000 active CPUs and the average capacity of each CPU is 1 GFLOPs.

revenues or reducing their costs. Increased revenues can be achieved through pricing strategies or by upgrading current services. For this dissertation, we concentrate on the latter, which means GSPs must acquire more resources. We presume that an upgraded service attracts both new and current clients, which can boost GSPs' revenues. This case usually occurs in busy GSPs that have high resource utilization. However, GSPs have to be careful not to overprovision, since resources might be idle for long periods of time. This raises the question on how many extra resources GSPs should acquire.

Instead of upgrading a service, GSPs might decide to downgrade their service to reduce their costs by reducing their computing resources. This case commonly happens in GSPs that have low resource utilization. The challenge is finding the lowest level of resources that is required to satisfy clients. If GSPs downgrade their quality of service (QoS) too much, they might end up losing their existing clients. To deal with these tradeoffs, GSPs have to know how clients value or rate their services. We believe that this information can help GSPs to estimate client demand for services in order to optimize their resource planning. Thus, this dissertation concentrates on how to extract this clients' value, which we refer to it as a value profile for a collection of grid clients.

As QoS is an essential attribute of demand and cannot be measured until after it is consumed, this situation is known as ex-ante opportunism[23]. In this situation, clients have information about some aspects of their satisfaction that GSPs do not (and vice versa). This makes it difficult for GSPs to estimate client demand. To improve this situation, feedback models, which work as

[23] Ex-ante opportunism frequently arises in a market for "experience goods", such as services which quality can only be evaluated after having consumed them [17]. In our case, clients cannot be assured about the true quality offered by GSPs until they have actually received the services. On the other hand, GSPs do not have an incentive to advertise any of their weak points. In fact, they have an economic incentive to over-advertise their QoS. With this knowledge, clients believe that all GSPs provide an average QoS and will not be willing to pay more than an average price. For example, clients, who need a high QoS, will not be willing to pay for a lower QoS and will not participate in the market.

signaling tools, are required [17]. With feedback models, clients are allowed to rate the received services based on their satisfaction. However, clients have to spend time to provide feedback, which can be considered as a kind of cost to them. If they cannot clearly see benefits from their contributions, they might not have an incentive to provide feedback. Furthermore, clients have incentives to provide untruthful feedback since they usually want to consume as many resources as possible. Thus, they might have an incentive to lie to receive a better service even though they may already be satisfied with the current service. Such conflict could lead to the questions on how client feedback can be used for this and how truthful client feedback can be obtained.

1.3. PROBLEM STATEMENT

The main theme of this dissertation is to develop an approach to build a value profile using feedback models for a collection of heterogeneous grid clients, which GSPs can use as a proxy for demand to plan their resources economically. The goals of this dissertation are to study how client demand can be estimated for services and how the cooperation can emerge. By understanding the conditions that allow it to emerge, it may be possible to suggest the development of cooperation in a particular set of conditions and provide the development of credibility-based binary feedback model for grid resource planning. Consequently, this dissertation is directed by the following key research questions:

- Does a value profile improve resource planning for GSPs?
- Does a value profile benefit clients?

- What information is valuable for GSPs? What can be obtained from clients? Is there a gap? If so, does it matter? Can/should the value profile be public?
- How can the binary feedback model be used to build a value profile? If so, under what circumstances?
- Do clients have an incentive to cooperate? If not, can an incentive be created? Does the incentive alter the optima of GSPs?
- Do clients have an incentive to be truthful? If not, can incentives/penalties be created? What is the impact of the incentives?

The outcome of this dissertation will create a useful value profile that can be used to estimate service demand for a collection of heterogeneous grid clients. A value profile will represent client's willingness-to-pay for grid resources so it will function as a proxy for a demand function. With the use of value profiles, it will assist GSPs when making capital investment decisions and help to accelerate an adoption of commercial grids.

1.4. DISSERTATION OUTLINE

This dissertation is organized as follows: Chapter 2 provides a background and a review of the available literature about grid resource management systems and grid resource allocation approaches. Chapter 3 presents research design, research questions, and experimental design. As stated in the research questions in Chapter 3, Chapter 4 presents theoretical frameworks and analysis tools used in this dissertation, which are binary feedback model, credibility mechanism, and game theory. Chapter 5 describes an approach to build a value profile using binary feedback for a collection of grid clients and justifies its concept. Chapter 6 explores significant issues related to the use of binary feedback for grid resource planning, which are mainly on cooperation and trust between GSPs and clients. The development of cooperation in a particular set of conditions and the development of credibility-based binary feedback model for grid resource planning are also presented in Chapter 6. Chapter 7 shows benefits of value profiles, limitations of results, and model implementations, respectively. Finally, Chapter 8 concludes this dissertation and discusses the future research.

2. GRID RESOURCE MANAGEMENT SYSTEMS

According to the complexities of grid resource allocation, researchers have developed multiple grid resource management systems (RMSs). The previous studies concentrate on both technical and techno-economic aspects. Krauter et al. [7] present the taxonomy and survey of non-economic-based grid RMSs, and Yeo and Buyya [39] present a summary of economic-based grid RMSs.

This dissertation mainly concentrates on commercial grids that allow clients to specify their QoS constraints; consequently, this chapter discusses only market-based RMSs. Section 2.1 reviews the state-of-art in market-based RMSs. Next, Section 0 reviews grid resource allocation approaches. Finally, Section 2.3 summaries the current literature and identifies the absent issues.

2.1. MARKET-BASED RESOURCE MANAGEMENT SYSTEMS

This section describes market-based RMSs using real-world market concepts to assign resources to clients based on a SLA. Figure 2.1 shows a traditional market-based RMS for commercial grids [2, 7, 8, 39]. The model consists of several core functions and two interfaces: *client interface* and *GSP interface*. A client submits a job (request) with specific QoS constraints (for example, budget and preferred duration) to the QoS broker via the client interface. Likewise, a

GSP manages its own resources or other's resources via the GSP interface. When the broker receives the job, it is responsible for examining the QoS constraints. Then, the admission control will decide whether to accept or reject the job based on system utilization. This is to ensure that the system is not overloaded and the job will be completed successfully.

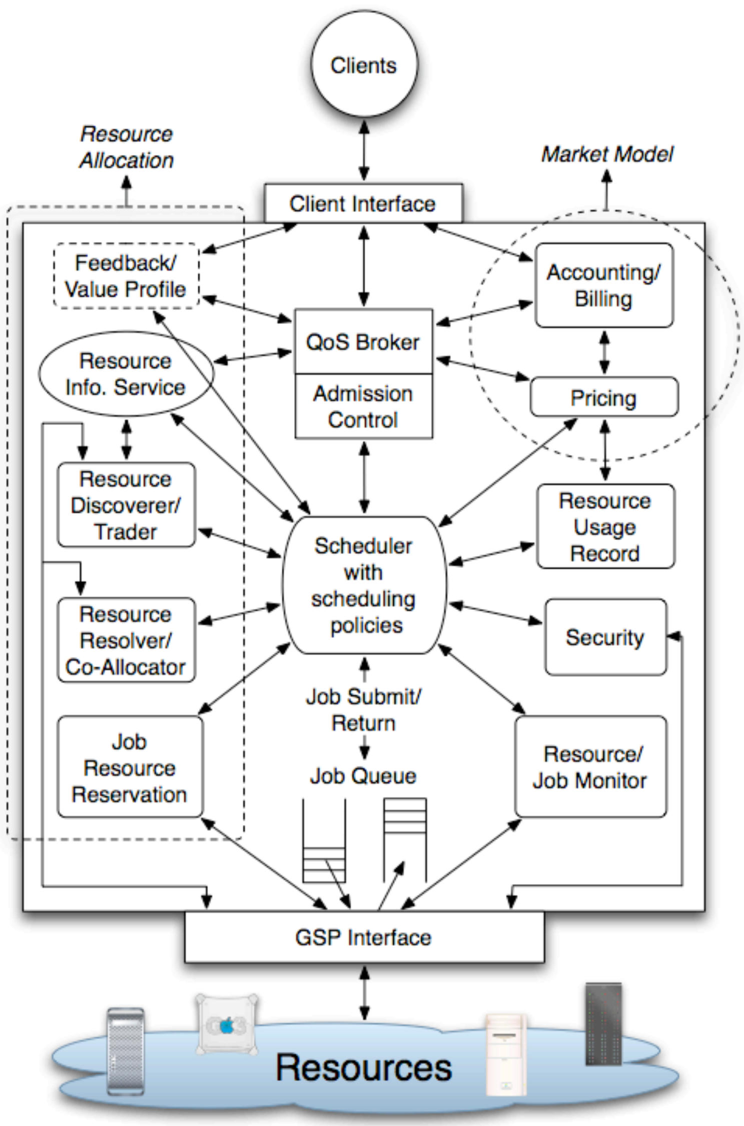

Figure 2.1 Interaction between components in a traditional market-based RMS for commercial grids.

The pricing mechanism determines how the job is charged, but more generally works as a tool for managing demand and supply. The way that the client negotiates a service price with the broker depends on a market model. Table 2.1 summarizes economic models used regularly in market-based RMSs [39].

The scheduler is responsible for resource discovery, resource trading, resource selection, job assignment, job resource reservation, and job monitor. The idea is to assign the job to the most appropriate resource based on SLA, scheduling policy, and pricing. The scheduler also tracks both resource and job status. The resource discoverer interacts with the resource information service to identify available resources. The co-allocator is required when making reservations of multiple nodes for a single job.

Table 2.1 Economic Model Description.

ECONOMIC MODEL	*DESCRIPTION*
Commodity Market	GSPs specify prices and clients pay for the resources that they consume. Prices can be flat or variable. A flat rate means that price is fixed for a certain time period, while a variable rate means that price changes dynamically based on the demand and supply at that time period.
Posted Price	Similarly to commodity market, the difference is that GSPs might advertise special offers to clients.
Bargaining	Both GSPs and clients negotiate an acceptable price.
Tendering / Contract-net	Clients announce their requirements to invite bids from GSPs. After evaluating the requirements, if GSPs are interested, they will respond with bids.
Auction	Clients bid service from one GSP. The type of auction can be first-price, Vickrey, Dutch, English, and double.
Bid-based Proportional Resource Sharing	Each client consumes a proportion of resources based on his/her bid.
Community / Coalition / Bartering	A group of GSPs or clients shares their own resources to build a cooperative sharing environment.
Monopoly and Oligopoly	A single GSP (monopoly) or a number of GSPs (oligopoly) decides the market price, where demand does not any affect on the price.

After the job is completed, the result is sent back to the scheduler. The resource information service will update the list of available nodes. The accounting mechanism calculates the computing cost and then charges the client for the resource that was actually consumed. Finally, the broker will return the result to the client along with the bill.

In this dissertation, we hypothesize that the inclusion of the value profile for a collection of clients into RMSs will assist the scheduler in allocating and planning resources more efficiently and effectively. We further hypothesize that this value profile can be constructed using a client suitably designed feedback mechanism. The feedback component will interact with the scheduler, the resource discoverer, and the co-allocator. Basically, clients will be allowed to leave feedback based on the received services via the client interface. The feedback component will collect all feedback information from clients and create a value profile, which will inform the scheduler. Then, the scheduler will update the resource discover or the co-allocator on how many resources it should acquire.

2.1.1. QoS Support

In telecommunications, QoS usually refers to qualities such as network bandwidth, delay, jitter, and throughput. However, in grid computing, it does not make sense to guarantee only network components since most grid jobs require high-performance computing capability or data storage and access. As a result, GSPs have to guarantee not only network components but also CPU processing cycles and data storage capacities of computing nodes.

An End-to-end QoS can be classified into three levels: *none*, *soft*, and *hard*. The first level, none is the same as best effort, which means services are not guaranteed. Soft QoS arises when the QoS broker establishes SLA, but cannot enforce all resources to meet the SLA requirements.

On the other hand, if the broker can enforce all resources to guarantee the SLA, it is called hard QoS. In short, most market-based RMSs support only soft QoS [39].

2.1.2. Survey of Market-based RMSs

Table 2.2 Summary of Grid Market-based RMSs.

System	*Economic Model*	*Brief System Description*
Bellagio	Auction	This system uses a centralized auctioneer to allocate resources to higher bidder first.
CATNET	Bargaining	Each client negotiates service price until a provider accepts it.
Faucets	Tendering / Contract-net	Clients are allowed to specify QoS contracts, and then bid for resources.
Gridbus	Commodity market	This system supports data-oriented applications, and allocates resources based on time or cost optimization.
Gridmarket	Auction	This system uses double auction where providers set floor prices and clients set ceiling prices.
Nimrod/G	Commodity market	This system allows clients to specify preferred duration and budget constraints. It allocates resources based on time or cost optimization.
NWIRE [10]	Auction	This system applies auction model to choose the best resources according to user QoS requirements.
OCEAN	Bargaining, Tendering/Contract-net	This system allows clients to find the best provider by using their negotiation mechanism.
Tycoon	Auction	This system use auction share that estimates proportional share based on latency-sensitive and risk-averse applications [39].

Yeo and Buyya [39] examine the applicability and suitability of existing market-based RMSs for supporting grid computing. Table 2.2 shows a summary of market-based RMSs, along with their adopted economic model. In this dissertation, we use a commodity market and a service price is variable.

2.2. GRID RESOURCE ALLOCATION APPROACHES

Grid resource allocation corresponds to on-demand provision of grid resources [15]. The task of resource allocation involves resource discoverer, resource co-allocator, and resource reservation. The objectives of resource allocation are (1) to acquire enough resource capacities for each job request with its QoS constraints, and (2) to optimize resource utilization. However, resource allocation is still a hard problem caused by sophisticated client behavior in term of willingness-to-pay for grid resources.

Researchers have proposed several resource allocation approaches; this section mainly discusses resource allocation approaches based on economic principles. Buyya [8] introduces GRid Architecture for Computational Economy (GRACE) to regulate demand and supply of available resources. His work concentrates on providing an incentive to resource owners to contribute resources and motivates resource users to consider a trade-off between computing cost and computing time. However, the author does not concentrate on how resource owners optimize their resource planning.

ChunLin and Layuan [9] concentrate on market-based resource allocation by investigating interactions between client agents, service agents, and resource agents. They present two-level market based resource pricing to optimize resource allocation. The two-level grid market is composed of a service market that regulates prices based on benefits of service agents and client agents, and a resource market that is charged for service agents and resource agents. The result shows that the two-level market outperforms a one-level market in terms of job completion time and resource allocation efficiency.

Gomoluch and Schroeder [13] investigate under which circumstances market-based resource allocation by continuous double auctions and by the proportional share protocol, respectively, outperforms a conventional round-robin approach. The results show that continuous double auctions perform the best in most cases. Wolski et al. [12] investigate G-commerce computational economies for controlling resource allocation in computational grid settings. They compare the efficiency of resource allocation between commodity markets and auctions. Their results indicate that commodity markets are a better option for controlling grid resources than auctions. Subramoniam et al. [18] use a commodity market based approach for resource allocation, and develop an algorithm to determine resource prices. For non economic-based work, Siddiqui et al. [15] introduce a mechanism of grid capacity planning for optimized QoS with negotiation-based advance reservation of grid resources.

In short, previous studies do not concentrate on how resource owners optimize their resource planning and how to extract a value profile for a collection of grid clients.

2.3. SUMMARY

This chapter reviews the literature of resource management systems and resource allocation approaches in grid computing. The previous studies concentrate on building market-based resource allocation, providing incentives to resource owners to contribute resources, motivating resource users to trade-off between budget and preferred duration, and investigating the efficiency of different market-based resource allocation in different aspects. None of them try to incorporate clients' perceived value. We believe that an appropriate framework requires to optimally plan resources based on the value profile.

3. RESEARCH DESIGN AND RESEARCH QUESTIONS

Given the review of market-based RMSs in Chapter 2, this chapter is designed to incorporate clients' value and to estimate demand for services. Section 3.1-Section 3.2 present the research outline and the research questions of this dissertation, respectively. Finally, Section 3.3 illustrates multiple sets of experiments with statistical testing.

3.1. RESEARCH OUTLINE

The main objective of this dissertation is to develop an approach to build a value profile using feedback models for a collection of heterogeneous grid clients, which GSPs can use as a proxy for demand to plan their resources economically. The objectives are to study how client demand can be estimated for services and how cooperation can emerge. The review of the literature on grid RMSs, in Chapter 2, shows that most previous work concentrated on market-based resource allocation without the use of the service value to grid clients. We believe that the use of this value profile will benefit both GSPs and clients. Consequently, this dissertation is directed by the following key research questions:

- Does a value profile improve resource planning for GSPs?
- Does a value profile benefit clients?

- What information is valuable for GSPs? What can be obtained from clients? Is there a gap? If so, does it matter? Can/should the value profile be public?
- How can the binary feedback model be used to build a value profile? If so, under what circumstances?
- Do clients have an incentive to cooperate? If not, can an incentive be created? Does the incentive alter the optima of GSPs?
- Do clients have an incentive to be truthful? If not, can incentives/penalties be created? What is the impact of the incentives?

Demand information is necessary for GSPs to optimally plan their resources but it is costly and difficult to estimate. In this dissertation, we propose a value profile to serve as a proxy for a demand function. To do so, we propose the use of binary feedback model to build the value profile for a collection of heterogeneous grid clients. The binary feedback model allows clients to rate GSPs based on quality of received services. This aggregate feedback would assist GSPs in achieving a better level of client satisfaction effectively and allocating their resources economically. Besides, clients would learn the true QoS of each GSP [17].

In reality, clients may not be truthful and cooperative. In most cases, feedback contributions do not directly benefit the feedback providers, while other entities benefit more directly. Thus, individuals have a little economic incentive to provide feedback even if it is socially optimal for them to do so [17]. Furthermore, clients have incentives to provide untruthful feedback since they usually want to consume as many resources as possible. Thus, they might have an incentive to lie to receive a better service even though they may already be satisfied with the current service. To deal with these issues, we propose the use of credibility mechanisms to detect untruthful feedback and penalize insincere or biased clients[24] [26].

Then, we have to study how the cooperation can emerge. By understanding the conditions that allow it to emerge, it may be possible to suggest the development of cooperation in a particular set of conditions and provide the development of credibility-based binary feedback model for grid resource planning. Thus, we also propose the use of game theory as a tool to construct and analyze strategic scenarios. In this dissertation, we concentrate on non-cooperative games of GSP vs. client and client vs. client. These games are non-zero sum games in which two players (GSP and client) can decide whether to cooperate with the other player or not. The only concern of each individual player is to maximize his/her payoff, without any concern for the other player's payoff.

We design this research by assuming that both GSPs and clients are rational and GSPs always prefer to cooperate. We also assume that commercial grid market is a competitive market where no GSPs or clients have the market power to influence prices. Both GSPs and clients know prices set by all GSPs, and they act independently. In this dissertation, we only concentrate on a particular interaction between GSPs and clients in the market.

The following describes more explicitly the research deliverables of this dissertation in the remaining chapters.

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[24] A bias is a prejudice in the sense for having a preference to one particular perspective, which is considered to be unfair. Dellarocas [55] classifies biased (or unfair) feedback into four cases: *unfairly high rating*, *unfairly low rating*, *negative discrimination*, and *positive discrimination*. Unfairly high rating results in an inflated GSP feedback profile while unfairly low rating results in an incorrectly low GSPs' feedback profile. Negative discrimination occurs when GSPs provide a good service to all clients except a few specific clients. On the other hand, positive discrimination occurs when GSPs provide remarkably a good service to a few selected clients and average service to others. According to the authors [55, 56, 57], unfair rating has a significant effect on feedback models that have a wide range of rating scales, such as Amazon.com. Since we will use binary feedback, there is less opportunity for unfairly high or low ratings.

- Chapter 4 reviews theoretical frameworks and analysis tools used in this dissertation. The key is to use the binary feedback model to construct value profiles and the credibility mechanism to detect untruthful feedback and penalize insincere or biased clients. We also use game theory to study cooperation and trust between GSPs and clients.
- Chapter 5 describes an approach to construct a value profile using binary feedback for a collection of heterogeneous grid clients, as hypothesized in the first research question in Section 3.2. The challenge is to justify whether the value profile can function as a proxy for a demand function.
- Chapter 6 identifies significant issues related to the use of binary feedback for grid resource planning, as hypothesized in the second and the third research questions in Section 3.2. With the use of game theory, we examine whether GSPs and clients have an incentive to cooperate and to be honest. The key is to study whether credibility mechanism can help the cooperation to emerge.
- The development and specification of the credibility-based binary feedback model are also presented in Chapter 6. The effect of untruthful feedback is also investigated in this Chapter by varying values of probability of contribution *P(contribution)*, probability of giving untruthful feedback *P(untruthful)*, and client's QoS threshold λ_j.
- Chapter 7 sets up experiments to determine benefits of the use of value profiles based on particular pre-assumptions in the forth and the fifth research questions in Section 3.2. We begin with building resource cost function from the TPC-C Benchmark[25] since it is required for resource optimization. The key is finding an economic equilibrium point to

[25] The Transaction Processing Performance Council (TPC) is a non-profit corporation founded to define transaction processing and database benchmarks. TPC-C Benchmark is an on-line transaction processing (OLTP) benchmark, which measures the performance of transaction processing systems. Available at http://www.tpc.org

acquire resources, which is the intersection of a demand curve and a long-run average total cost (LATC) curve. The results and discussions are also given in this Chapter.

- The results from the experiments can be referenced to demonstrate how value profiles will benefit both GSPs and clients. The main contribution of this work is the credibility-based binary feedback model that can be used to construct value profiles, which will help GSPs optimize their long run resource investment and help to accelerate an adoption of commercial grids.

3.2. RESEARCH QUESTIONS

This section describes five research questions according to the use of credibility-based binary feedback model for grid resource planning.

- **(Q1)** Can the binary feedback model be used to construct a useful value profile for GSPs? In other words, binary feedback can be used as a proxy for demand.
    - **(Q1.1)** From clients' perspective, can the number of jobs with positive feedback in each price range represent an inverse demand curve and function as a proxy for a demand function?
    - **(Q1.2)** From GSPs' perspective, can clients' feedback information represent an inverse demand curve and function as a proxy for a demand function?

- **(Q2)** Do clients have incentives to cooperate? In other words, clients have incentives to provide untruthful feedback to maximize their payoffs. Given feedback game[26], if both the client and the GSP are rational, then $payoff_{client}$ *(truthful feedback)* > $payoff_{client}$ *(untruthful feedback)*.

- **(Q3)** Can credibility mechanisms be used to encourage clients to be truthful? In other words, credibility mechanisms are required for the cooperation to emerge. Given the credibility-based feedback game[27], $payoff_{client}$ *(truthful feedback)* > $payoff_{client}$ *(untruthful feedback)*.

- **(Q4)** Does a value profile improve resource planning for GSPs?
  - **(Q4.1)** Does the use of value profiles result in an increment of GSP's profit $profit_i$? In other words, given *without_value_profiles* and *with_value_profiles* scenarios, then $profit_i^{with\_value\_profiles} > profit_i^{without\_value\_profiles}$.
  - **(Q4.2)** Does the use of value profiles result in a decrement of idle resources? In other words, given *without_value_profiles* and *with_value_profiles* scenarios, system utilization ρ_i increases $\rho_i^{with\_value\_profiles} > \rho_i^{without\_value\_profiles}$.
  - **(Q4.3)** Does the use of value profiles result in an increment of client satisfaction rate? In other words, given *without_value_profiles* and *with_value_profiles* scenarios, percentage of positive feedback $\%pos\_fb_i$ increases $\%pos\_fb_i^{with\_value\_profiles} > \%pos\_fb_i^{without\_value\_profiles}$.

[26] See Section 6.2.3
[27] See Section 6.2.4

- **(Q5)** Does a value profile benefit clients?
  - **(Q5.1)** Does the use of value profiles result in an increment of clients' job success rate? In other words, given *without_value_profiles* and *with_value_profiles* scenarios, clients' job success rate $\%job_{success,\,j}$ increases $\%job_{success,\,j}^{with\_value\_profiles} > \%job_{success,\,j}^{without\_value\_profiles}$.

3.3. ANALYTICAL AND EXPERIMENTAL DESIGN

This section describes how we test the five research questions. To do so, we create three sets of experiments. The first set is designed to test the research question Q1. We perform this experiment by varying service prices, clients' maximum budgets, and clients' maximum preferred durations. Then, we measure the mean number of jobs with positive feedback. Table 3.1 summarizes factors used in this full factorial design with 100 replications. Figure 3.1 presents the algorithm design using in the first experiment set.

The second set is designed to test the research questions Q2 and Q3. We design non-cooperative games to study cooperation and trust of GSP vs. client and client vs. client. In the feedback games, the GSP has to decide either *Trust* or *Don't trust* clients' feedback. The client has to decide to provide either *Truthful* or *Untruthful* feedback. Then, we apply the concept of credibility mechanisms into the feedback games to observe whether the cooperation can emerge.

The third set is designed to test the research questions Q4 and Q5 by varying job loads, service rates, and values of probability of giving untruthful feedback *P(untruthful)*. Then, we measure the mean of ρ_i, $\%pos\_fb_i$, and $\%job_{success,\,j}$ when not using value profiles, and compare these results to when using value profiles. Table 3.2 summarizes factors used in this full factorial design with 50 replications. Figure 3.2 shows the algorithm design using in this experiment. For statistical testing on this experiment set, we perform paired *t*-test on the mean of results, as summarized in Table 3.3. For $profit_i$ judgment, we draw a graph based on the mean of total revenue and total cost.

Table 3.1 Full Factorial Design for Q1

Factors	*Levels*
p_i (service prices)	• (Q1.1) $p_i = \{0.1, 0.2, 0.3, \ldots, 1.0\}$ • (Q1.2) p_i is varied based on system utilization
max_budget	{10, 20}
max_preferred_duration[28]	{5, 20}
# of experiments	$11 \times 2 \times 2 \times 100 = 4{,}400$

Table 3.2 Full Factorial Design for Q4 and Q5

Factors	*Levels*
Job Load	• Low demand o NUM_CLIENTS = 5,000 o Interarrival rate = 0.3 jobs/min • High demand o NUM_CLIENTS = 50,000 o Interarrival rate = 0.5 jobs/min
Service Rate (jobs/min)	{0.24, 0.40, 0.84, 1.25, 1.62, 2.20}
P (untruthful)	{0, 1}
# of experiments	$2 \times 6 \times 2 \times 50 = 1{,}200$

[28] The value of maximum budget and preferred duration can be any number. We select these ranges of values so that we can observe how a demand curve shifts when clients increase or decrease their constraints.

Table 3.3 Statistical Testing Methods

Research Question	*Dependent Variable*	*Method*
Q4.2	ρ_i	Paired *t*-test on the mean of dependent variable
Q4.3	$\% pos\_fb_i$	Paired *t*-test on the mean of dependent variable
Q5.1	$\% job_{success,\, j}$	Paired *t*-test on the mean of dependent variable

```
Algorithm Design for Q1

SET each client's constraint  (budget, preferred_duration, and no_of_jobs)
FOR all clients' job
  WHILE a client still has jobs to submit
      server announces server_estimate_price and server_estimate_computing_time
      IF client_remain_budget ≥ server_estimate_price THEN
          CALCULATE possible_job_done if a client submit his/her job at this price
          IF client_remain_jobs ≤ possible_job_done THEN
              IF  preferred_duration ≥ server_estimate_computing_time THEN
                  SUBMIT job to queue
                  WAIT until job is done
                  DECREASE no_of_jobs
                  RECORD total_service_price and total_computing_time
                  CALCULATE satisfaction
                  PROVIDE feedback based on the satisfaction
                  IF satisfaction ≥ 0 THEN
                      feedback = 1 (positive)
                      COUNT no_of_jobs_with_positive_feedback
                  ELSE IF satisfaction ≤ -λj THEN
                      feedback = 0 (negative)
                      COUNT no_of_jobs_with_negative_feedback
                  ELSE IF -λj < satisfaction < 0 THEN
                       NO RATE
                  END IF
                  CALCULATE client_remain_budget
                  IF client_remain_budget ≥ 0
                      Repeat submitting job process
                  END IF
              ELSE
                      WAIT for other period
              END IF
          ELSE
              WAIT for other period
          END IF
      ELSE
          WAIT for other period
      END IF
  END WHILE
END FOR
```

Figure 3.1 Algorithm design for Q1.

Algorithm Design for Q4 and Q5

1. Client *j* decides whether to submit a job based on his/her constraint, as presented in Figure 3.1.

2. Scheduler: After receiving job from client *j*, the scheduler will check the *pun_state* of that client.

```
IF pun_state=false THEN
    the scheduler will start process that job.
ELSE
    the job will be hold during punishment period (tp) before start processing.
ENDIF
```

2. Binary feedback: When the job is completed, the client will be asked to provide feedback based on the received service.

```
IF pun_state=false THEN
    the client is allowed to provide feedback
    the client provides feedback based on his/her satisfaction (Sj),
    CALCULATE satisfaction, Sj()

        IF Sj ≥ 0 with P(contribution) THEN
            he/she rates positive "1"
        ELSE IF Sj ≥ 0 with (1-P(contribution)) THEN
            he/she does not rate
        ELSE IF Sj ≤ -λj (client threshold) with P(contribution) THEN
            he/she rates negative "0"
        ELSE IF Sj ≤ -λj with (1-P(contribution)) THEN
            he/she does not rate
        ELSE IF -λj < Sj < 0 with (1-P(untruthful)) THEN
            he/she does not rate
        ELSE IF -λj < Sj < 0 with P(untruthful) THEN
            he/she rates negative "0"
        ENDIF

ELSE
    the client is not allowed to provide feedback since he/she is under punishment.
    RESET pun_state=false
    RETURN
ENDIF
```

3. Credibility mechanism: GSP will check the received feedback $FB_j^{received}$ by comparing with the expected feedback $FB_j^{expected}$ based on the performance record $t_j^{computing}$

IF $FB_j^{received} = FB_j^{expected}$ THEN

```
        COUNT this feedback information
        UPDATE value profile
        CALCULATE the percentage of positive feedback
ELSE
        DISCARD this feedback information
        punish this client
        SET pun_state=true
ENDIF
```

4. Resource allocation: GSP will use the value profile as a proxy for a demand function to find equilibrium point to optimally acquire resources.

Figure 3.2 Algorithm design for Q4 and Q5.

4. THEORETICAL FRAMEWORKS AND ANALYSIS TOOLS

This chapter reviews theoretical frameworks and the analysis tools used in this dissertation. To construct a value profile that is useful to GSPs, we use binary feedback, which is a form of on-line reputation. Thus, in this chapter, we examine the prior research on binary feedback and introduce the way in which binary feedback can be used to construct the value profile. First, Section 4.1 discusses online reputation mechanisms and their effects. Then, Section 4.2 presents the use of binary feedback model as the framework to understand a client satisfaction and to build the value profile. The concept of value profiles is introduced in Section 4.2.1. Next, Section 4.3 presents the use of credibility mechanisms to handle insincere or biased clients. Finally, Section 4.4 describes game theory as the tool to study conflict and cooperation in resource planning, following Turocy and Stengel [21].

4.1. ONLINE REPUTATION

Online reputation mechanisms, also known as feedback systems, have been emerged as a significant quality signaling and a control mechanism in private e-markets such as eBay[29] and

[29] www.ebay.com

Amazon[30] [17, 24]. The objective of reputation mechanisms is to encourage trust and cooperation in online trading communities. Reputation systems are designed to collect feedback information from individual traders' past behavior and publish it to communities as an individual feedback profile. This profile is available for potential future trading parties to assess trustworthiness and reliability. The success of future transactions depends on how people behave today. It is not only with their recent partner, but also others as well.

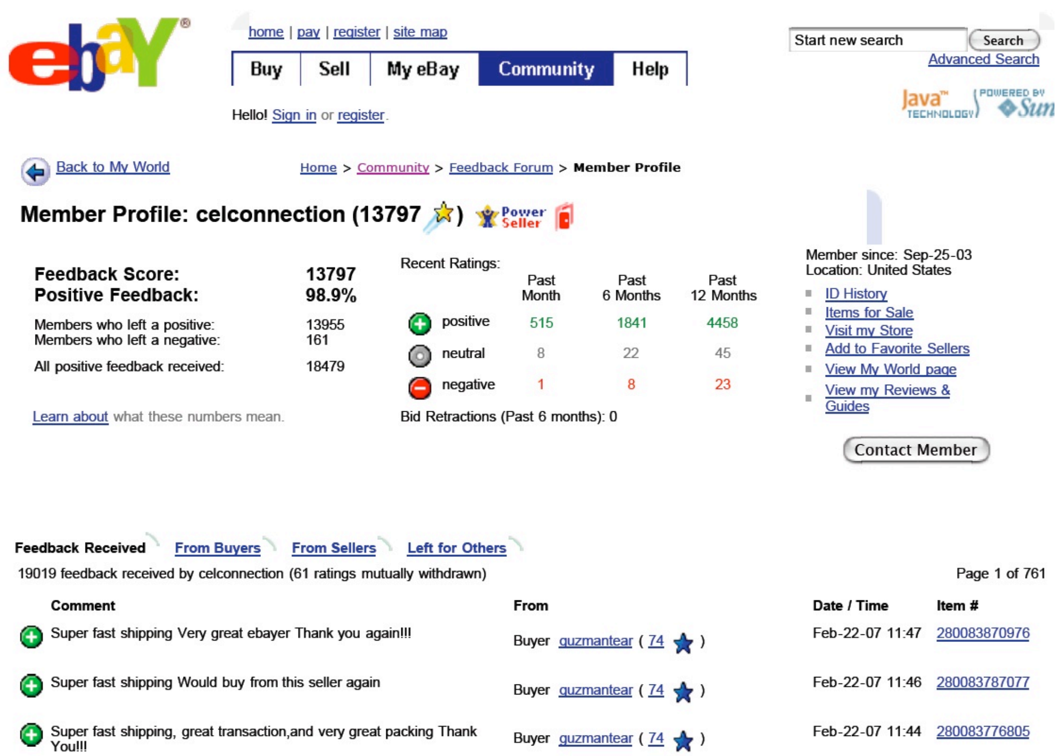


Figure 4.1 A typical eBay member's ID and member profile, as of Feb 2007.

The willingness of buyers to bid on or pay for items is a function of quality, a utility[31] of goods (or services) and a risk of "bad" transaction[32] being traded [52]. Thus, sellers are required

[30] www.amazon.com

[31] In economics, utility is a measure of the satisfaction or happiness gained by consuming goods and services.

to provide buyers with sufficient information about their product and transaction quality. In the same way, buyers are required to provide sellers with their transaction history since sellers prefer to sell products to buyers who do not have any bad transaction history.

Today, the most well-known feedback mechanism is the one used by eBay. Since transactions in eBay are not contractual guarantees, traders trust other trading parties according to their member profiles, as shown in Figure 4.1. eBay uses a two-way feedback mechanism that buyers and sellers can rate one another at the end of transactions. The ratings can be negative (-1), neutral (0), or positive (+1). eBay users also have opportunity to leave short text comments, and rated partners can respond to unfair comments. These ratings summarize into an individual feedback score by taking the sum of positive ratings minus the sum of negative ratings. eBay uses the feedback score as a reputation indicator of individual member in its community.

4.1.1. The Effect of Online Reputation

Normally, a reputation score of sellers is an indication of the trustworthiness of sellers even though it is based on past transactions, not the current one. A number of studies have observed how eBay reputations affect sale prices. Resnick et al [52] summarized related studies on the impact of reputation on price and probability of sale. Most results indicate that positive feedback increases price and probability of sale. On the other hand, negative feedback decreases price and probability of sale.

For example, Melnik and Alm [51] conclude that sellers with the better reputation can expect to receive a higher price for an auction good. Similarly, Lucking-Reiley et al [53] present an exploratory analysis of determinants of prices in eBay. They conclude that sellers' feedback

[32] A "bad" transaction is one that fails after the auction closes or where the product or service does not measure up to expectations.

ratings have an effect on auction prices. Positive feedback ratings have a smaller effect than negative feedback ratings do. This means that eBay users concentrate on sellers' negative feedback ratings. The authors find that

> 1% increase in the seller's positive feedback ratings yield a 0.03% increase in the auction price on average…in the opposite direction, 1% increase in the seller's negative feedback ratings causes a 0.11% decrease in auction price on average.

A client usually has a particular point of view or an ideological perspective when providing feedback. The larger the interval rating scale[33], the more the level of complexity of an individual preference will increase. For example, given a rating scale 1-10, "10" does not mean the same thing to all clients. Besides, rating "7" and "8" might be huge different or indifferent based on clients' perspective. To simplify this complexity, we use the binary feedback model, which has only "0" and "1", in this dissertation.

4.2. BINARY FEEDBACK MODEL

Similar to eBay's feedback mechanism, the binary feedback model is a mechanism where clients (buyers) can only rate past transactions as either "positive" (1) or "negative" (0). Positive ratings indicate that clients received high quality or satisfactory services (or goods), and negative ratings indicate that clients received low quality or unsatisfactory services. The summary of ratings is publicly available to all clients. As a result, clients know the quality of GSPs (sellers) based on the summary of their most recent ratings [25].

According to Dellarocas [24], quality can be divided into three categories; *real quality* (q_r), *advertised quality* (q_a), and *estimated quality* (q_e). Real quality is unknown to clients in advance

[33] Rating scales are a set of numbers broadly used to obtain indications of client opinions of services. The objective is to extract information that is considered to reflect the magnitude of the perceived QoS [62].

and can only be determined after consumption. Generally, clients prefer higher quality to lower quality, although their willingness to pay for extra quality varies. Advertised quality, controlled by GSPs, informs clients through advertising, and it may or may not relate to real quality. Estimated quality is determined from the information that is available to clients. In conlusion, clients can estimate the quality from advertised quality and GSPs' rating profile.

This quality information can be used to calculate client satisfaction, which is the difference between real quality and estimated quality. A client decides whether to rate a transaction based on satisfaction (S_j). If the real utility exceeds the expected utility ($S_j>0$), the client should rate that transaction as positive. On the other hand, if the real utility falls below some threshold (λ_j) of the expected utility ($S_j \leq -\lambda_j$), the client should rate that transaction as negative. Furthermore, if the client receives slightly bad but not very bad service ($-\lambda_j<S_j\leq 0$), the client may not provide any feedback [24].

In this dissertation, we adopt this approach to allow clients to report their satisfaction or dissatisfaction with their service consumption.

4.2.1. Value Profiles

Since the demand function either for a client or for a group of clients is hard to obtain, most studies assume a utility function and use it to calculate the price that clients are willing to pay. We assert that a feasible way to obtain the willingness to pay of clients is to use feedback models such as the binary feedback model. As discussed in Section 4.2, positive feedback implies that a client is satisfied with the received service in term of cost and time, and he/she is willing to pay for such service at another future time. Negative feedback implies that a client is unsatisfied with the received service, and he/she may not be willing to pay for such service again. Therefore, in this dissertation, we propose the use of binary feedback to deduce the willingness to pay for a collection of clients.

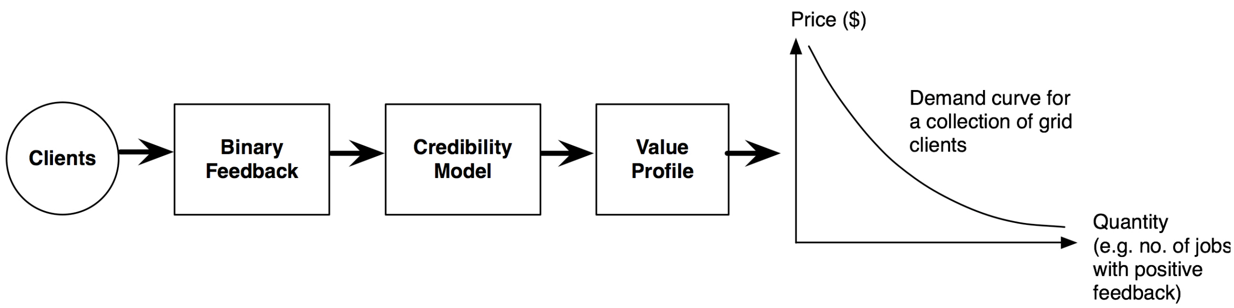


Figure 4.2 The concept of value profiles.

By obtaining feedback information, as presented in Figure 4.2, GSPs can create a value profile that can be used as a proxy for demand for a collection of heterogeneous grid clients. This value profile will collect and tabulate satisfactory feedback as a function of price. We will show that this value profile represents the willingness to pay of clients at different prices so it can function as a proxy for a demand function. However, since clients may not be truthful and cooperative, GSPs have to filter out the untruthful feedback to improve an accuracy of value profiles. Therefore, the use of credibility mechanisms is proposed to detect undesired feedback and penalize insincere or biased clients, as discussed in the following section.

4.3. CREDIBILITY MECHANISMS

Since trust is a significant issue in grid computing, many studies have been done in this area [41, 42, 43, 44, 45, 46]. For example, Weiss and Huang [11] present different trust requirements in various grid models. They concentrate on both non-security related expectations (e.g. matching, accounting) and security related expectations (e.g. authorization, authentication, free of spyware and virus).

In this dissertation, we concentrate on client's feedback trustworthiness. We propose the use of credibility mechanisms that allow GSPs to detect and penalize insincere or biased clients, who intend to lie to receive better services. The objective is to ensure that sincere clients will always receive more benefit than insincere clients.

We adopt the credibility mechanism that is proposed by Papaioannou and Stamoulis [26], as shown in Figure 4.3. The authors introduced a *non-credibility (ncr)* and a binary *punishment_state* variable to punish insincere clients and limit potential unfairness. Entering a system, each client is assigned a moderately high initial non-credibility value ncr_0 (a lower *ncr* is the better). The initial *punishment_state* of each client is *false*, which means that an individual is not being punished. To enter grid computing process, a *punishment_state* has to be *false* and a *ncr* value has to be less than or equal to an *accepted credibility (acr)*.

After a transaction, a client rates the GSP either positive or negative. Then, the GSP checks whether the received feedback (f_c) is reliable or not by comparing that feedback with its quantifiable performance (f_{gsp}). If the GSP disagrees with the feedback ($f_c \neq f_{gsp}$), the client's *ncr* value is increased by x ($ncr = ncr+x$), and he/she is punished (*punishment_state* = *true*) for some periods of time and the untruthful feedback is discarded. During the punishment period, the client cannot process any transaction. On the other hand, if the client's feedback is consistent with the quantifiable performance ($f_c=f_{gsp}$), the value of client's *ncr* is decreased by y ($ncr = ncr-y$), where $0<y<x$ and $ncr>0$ and the truthful feedback is sent to the reputation system. This process repeats when a new job enters a system.

On the other hand, GSPs might have an incentive to cheat and disregard unfavorable feedback, which we will analyze in Section 6.3.

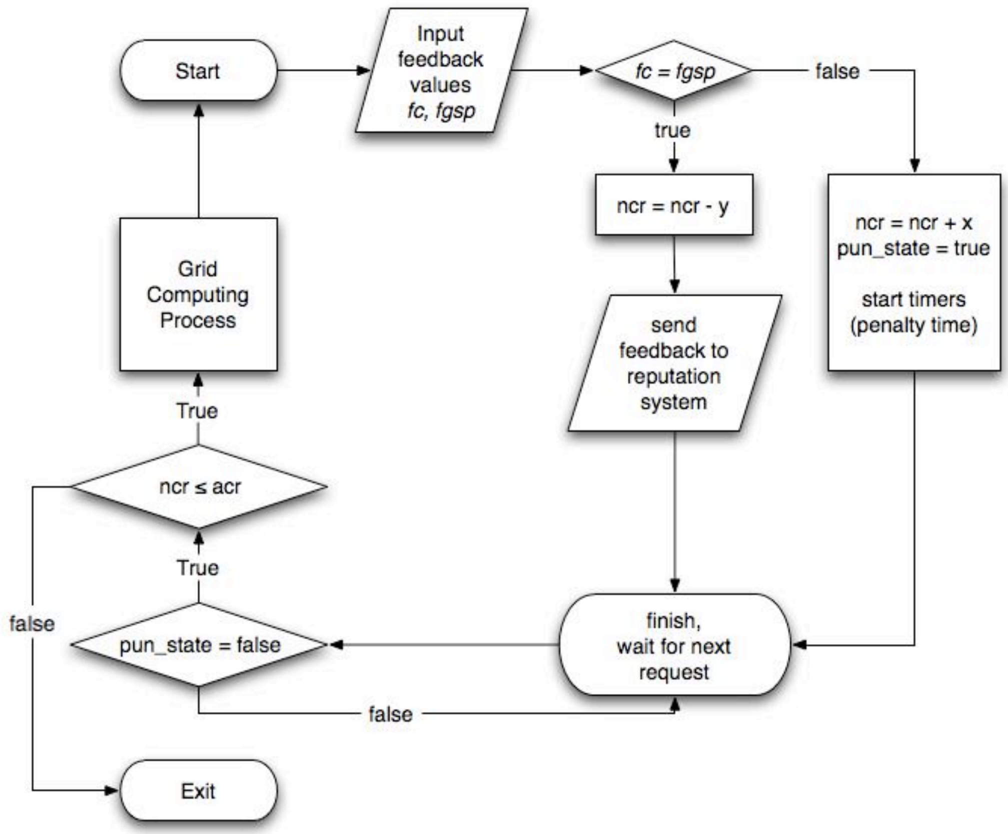


Figure 4.3 Credibility mechanism, modified from [26].

4.4. GAME THEORY

Game theory has been applied in many different research areas, for example, political science, political economy, public choice, economics and business, biology, sociology, philosophy, logic, and computer science. In computer science, researchers use game theory to study trustworthy behavior in transactions [23, 47, 48, 49]. In this dissertation, we use game theory to analyze cooperation and trust between GSP vs. client and client vs. client.

Game theory[34] is the formal study of conflict and cooperation and can be applied wherever players choose different actions based on their interest. The players can be individuals, groups, firms, organizations, or any combination of these. The purpose of game theory is to formulate, construct, analyze, and understand strategic situations.

Games consist of a set of players, a set of strategies available to those players, and the specification of payoffs for each strategy combination. A classic assumption of games is that all players are rational, which means that they make choices based on their maximum payoff. The objective of game analysis is to forecast how rational players play games against each other. However, dominant strategies do not always exist. Thus, the Nash equilibrium (NE) is a solution where no player can improve their payoff by changing their strategy unilaterally.

Games can be represented in two different forms: *Strategic Form* and *Extensive Form*. Strategic games are a principal form for non-cooperative games with rational players. As shown in Figure 4.4(a), these games are represented by a matrix, which lists each player's strategies and payoffs with every possible combination of choices. Payoffs can be determined from each player's utility function. These games usually assume that both players move simultaneously, or that later movers do not have any information about the earlier players' moves.

Extensive games are a game tree, as presented in Figure 4.4(b). These games are sequential games, where later players have information about earlier moves. The information can be either perfect or imperfect. In general, these games can be analyzed in their form or in strategic form.

[34] The field of game theory was established by the 1944 publication Theory of Games and Economic Behavior by John von Neumann and Oskar Morgenstern [22]. In 1950, John Nash proved that finite games always have an equilibrium point, given that players choose actions that are the best payoff for them.

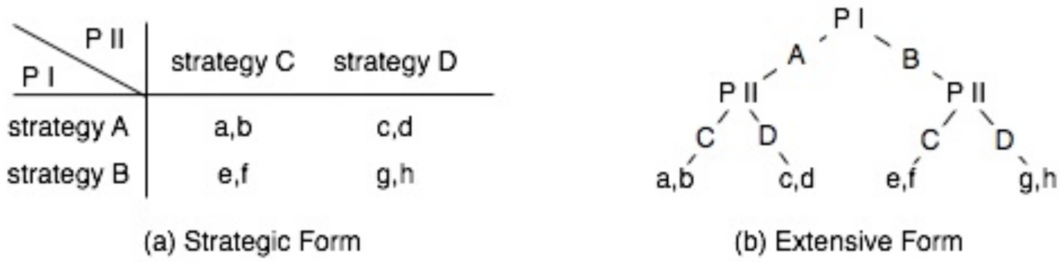


Figure 4.4 Game theory models.

Extensive games with perfect information can be analyzed using the backward induction method starting from root of a game tree. Backward induction commonly specifies unique choices at the players' decision nodes. However, if a player has two or more indifferent choices at a node, he/she may randomly make a move. This affects the earlier player since his/her payoff depends on the later player. In this case, the backward induction becomes an inappropriate method. Moreover, not all Nash equilibria can be found using the backward induction method. As a result, these games have to be converted into their equivalent strategic forms. With this transformation, these games are analyzed in a complete move plan and all strategic combinations are analyzed to result in a set of feasible Nash equilibria.

5. VALUE PROFILES

Given the first research question Q1, this chapter describes an approach to construct a value profile using binary feedback for a collection of heterogeneous grid clients. To develop the approach, we must first build a simple model of GSPs and clients. Using these simple models, we can show that a value profile is useful for grid resource planning. Since they are economic actors, we refer to them as GSP agents and client agents. GSP agents are resource owners who manage all grid resources and client agents are resource users who request a service and pay for received service. The specifications of GSP agents and client agents are given in Section 5.1-Section 5.2, respectively. Then, Section 5.3 describes assumptions made for this dissertation and justifies the concept of value profiles, respectively. Finally, Section 5.4 summarizes this chapter.

5.1. GSP AGENTS

GSP agents provide services to clients based on a SLA. In each period, the agents announce an estimated service price to clients. For this dissertation, the price varies based on the utilization of system, which we express as [54]

$$p_i^{est} = a_i + b_i * \left(\rho_i \big/ (1 - \rho_i) \right) \tag{5.1}$$

The agents also announce an estimated computing time, which we take to be the mean response time of the system. Table 5.1 provides notations and parameters of GSP agents.

Table 5.1 General Parameters of GSP Agents.

Symbol	*Description*
i	GSP index
p_i^{est}	Estimated price for computing a job in that period, which equals an estimated cost to the client
a_i	Constant for adjusting pricing range
b_i	Constant for adjusting pricing range
ρ_i	Average utilization of system i in that period

5.2. CLIENT AGENTS

We assume that clients are usually satisfied when a job is completed within their preferred duration and budget. Thus, the client satisfaction can be calculated from the difference between the change in computing time ($\%\,\Delta\, t_j^{computing}$) and the change in computing cost ($\%\,\Delta\, C_j^{computing}$). The change in computing time is defined as percentage of the difference between preferred duration ($t_j^{preferred\_duration}$) and total computing time ($t_j^{total\_computing}$), while the change in computing cost is defined as percentage of the difference between job budget ($c_j^{\exp}$) and real cost (c_j^{real}). Since clients have different budget and preferred duration constraints, we also include constraint sensitivity ($\propto_j$) in the calculation. Consequently, we express client satisfaction (S_j) as (see Table 5.2 for the summary of notations and parameters of client agents)

$$S_j = \alpha_j * \left(\%\ \Delta\ t_j^{computing}\right) - \left(1-\alpha_j\right) * \left(\%\ \Delta\ C_j^{computing}\right) \tag{5.2}$$

where

$$\%\Delta t_j^{computing} = \left(t_j^{preferred\_duration} - t_j^{total\_computing}\right) \Big/ t_j^{preferred\_duration} \tag{5.3}$$

$$\%\ \Delta\ C_j^{computing} = \left(c_j^{\exp} - c_j^{real}\right) \Big/ c_j^{\exp} \tag{5.4}$$

Table 5.2 General Parameters of Client Agents.

Symbol	*Description*
j	Client index
S_j	Service satisfaction of client j after his/her job is completed
$\propto_j$	Constraint sensitivity of client j
$t_j^{preferred\_duration}$	Preferred duration for completing a job of client j
$t_j^{total\_computing}$	Total computing time for completing a job of client j
$\%\ \Delta\ t_j^{computing}$	Percentage of the difference between preferred duration and total computing time for completing job of client j
$c_j^{\exp}$	Expected cost (job budget) for completing job of client j
c_j^{real}	Real cost for completing job of client j
$\%\ \Delta\ C_j^{computing}$	Percentage of the difference between expected cost (job budget) and real cost for completing job of client j
FB_j	Binary feedback of client j
λ_j	QoS threshold of client j

Unless otherwise specified, we assume that clients are truthful and cooperative. According to Section 4.2, after a service, each client provides binary feedback FB_j based on the value of his/her satisfaction, which is expressed as (see Table 5.2 for the summary of notations and parameters of client agents)

$$FB_j = \begin{cases} \text{"1"} & \text{if} \quad S_j \geq 0 \\ \text{"0"} & \text{if} \quad S_j \leq -\lambda_j \\ \text{no rate} & \text{if} \quad -\lambda_j < S_j < 0 \end{cases} \tag{5.5}$$

5.3. ASSUMPTIONS AND JUSTIFICATIONS

We make a number of simplifying assumptions in this dissertation so that we can concentrate on the proof of the concept of value profiles. Some of these assumptions can be relaxed in future research. First, we offer jobs to the grid from heterogeneous clients that have different budgets and preferred durations. As shown in Figure 3.1, clients will decide whether to submit a job based on GSPs' service announcement subject to clients' constraints. We also assume that each client has a different number of jobs to process and is able to submit only one job at a time. Then, we assume that jobs have the same size. For this experiment, we also assume that clients are cooperative and truthful.

To simplify the model, we use a M/M/1 queuing system with First Come First Serve (FCFS) policy, which means that there is only one GSP in this commodity market. Thus, the price increases when the system utilization increases: the price is high during peak periods (high utilization) and low during off-peak periods (low utilization). This helps to regulate demand by encouraging clients who have low budgets and long preferred durations to wait for an off-peak period. However, some clients might prefer paying high costs to receive results as soon as possible. We also assume that having another GSP will not affect an outcome since prices dynamically change based on system utilization that corresponds to client demand.

In this dissertation, like purchasing airline tickets[35], we assume that prices will be fixed after GSPs and clients have an agreement but the completion time is uncertain. Thus, the estimated service cost is the same as the final cost ($\%\Delta C = 0$). We also assume that there is no discount rate for clients when GSPs miss a preferred duration because we want a true client satisfaction. Moreover, we assume the market is a competitive market.

To justify the concept of value profiles in Section 4.2.1, we conducted the first set of experiments to determine whether value profiles are consistent with the demand theory. Table 5.3-Table 5.4 present the values of parameters and the design for the first research question, respectively. The results are presented as the mean number of jobs with positive feedback in each price range.

Figure 5.1-Figure 5.2 show the resulting value profiles from the clients' perspective and the GSPs' perspective, respectively. The curves clearly have the shape of typical demand functions since the number of jobs with positive feedback and the number of total jobs submitted to the system are inversely proportional to the service prices. Moreover, these curves shift up and to the right when clients increase their maximum budget or preferred duration (and vice versa).

From the clients' perspective, at a price of 0.4, if they increase their budget from 10 to 20, the number of jobs with positive feedback and the number of total submitted jobs will increase from 136 to 323 and from 174 to 441, respectively, as shown in Figure 5.1(a). If clients also increase their preferred duration from 5 to 20, the number of jobs with positive feedback and the number of total submitted jobs will increase to 531 and 633, respectively, as shown in Figure 5.1(b).

---

[35] When purchasing airline tickets, we pay a certain price but we do not know whether a flight will be delayed.

Table 5.3 Model Parameters for Research Question Q1

	Parameters	*Values*
ENVIRONMENT	*NUM_CLIENTS*	100
	Interarrival rate	0.6 jobs/min
	Service rate	1.0 jobs/min
CLIENT AGENTS	*Budget*	Uniform (1, *max_budget*)
	Preferred duration	Uniform (1, *max_preferred_duration*)
	No_of_Jobs	Uniform (1, 50)
	λ_j (client's QoS threshold)	0
	α_j	1
	$t^{retransmit}$	1000 min
	P(contribution)	1
	P(untruthful)	0
GSP AGENTS	a_i	0
	b_i	0.1

Table 5.4 Full Factorial Design for Research Question Q1

Factors	*Levels*
p_i (service price)	• (Q1.1) p_i = {0.1, 0.2, 0.3, … , 1.0}
	• (Q1.2) p_i vaires based on system utilization
max_budget	{10, 20}
max_preferred_duration	{5, 20}

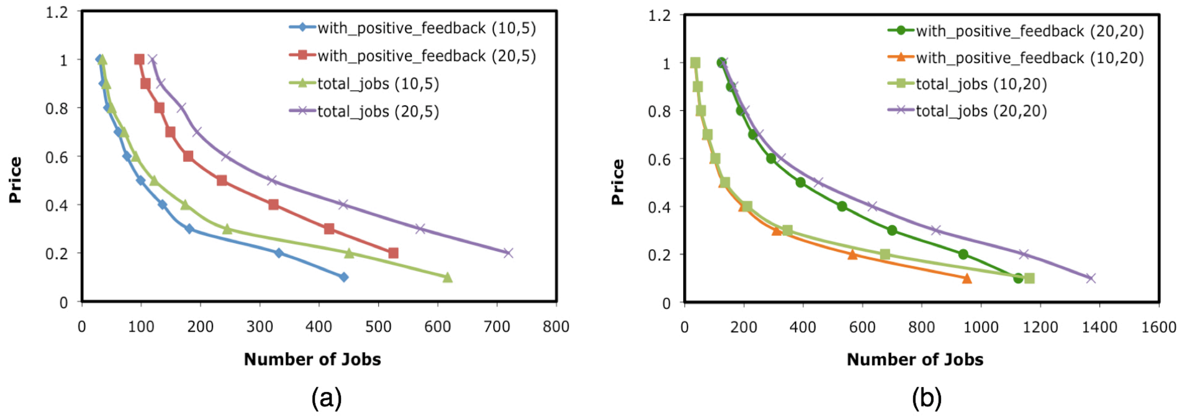


Figure 5.1 Demand curves based on value profiles from the clients' perspective (a) *max_budget* = {10, 20} and *max_preferred_duration* = {5} (b) *max_budget* = {10, 20} and *max_preferred_duration* = {20}.

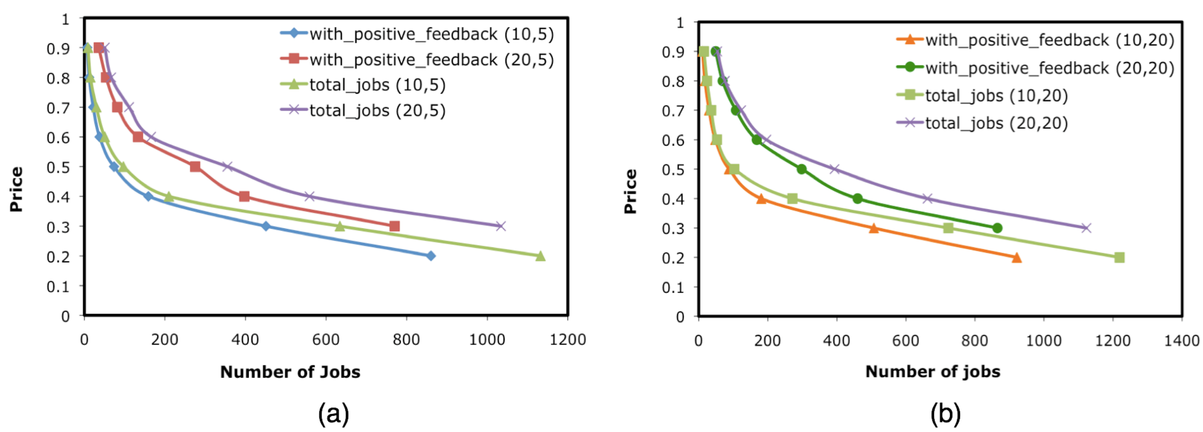


Figure 5.2 Demand curves based on value profiles from the GSPs' perspective (a) *max_budget* = {10, 20} and *max_preferred_duration* = {5} (b) *max_budget* = {10, 20} and *max_preferred_duration* = {20}.

From the GSPs' perspective, at a price of 0.3, if clients increase their budget from 10 to 20, the number of jobs with positive feedback and the number of total submitted jobs will increase from 451 to 770 and from 634 to 1035, respectively, as shown in Figure 5.2(a). If the clients also increase their preferred duration from 5 to 20, the number of jobs with positive feedback and the number of submitted jobs will increase to 865 and 1123, respectively, as shown in Figure 5.2(b).

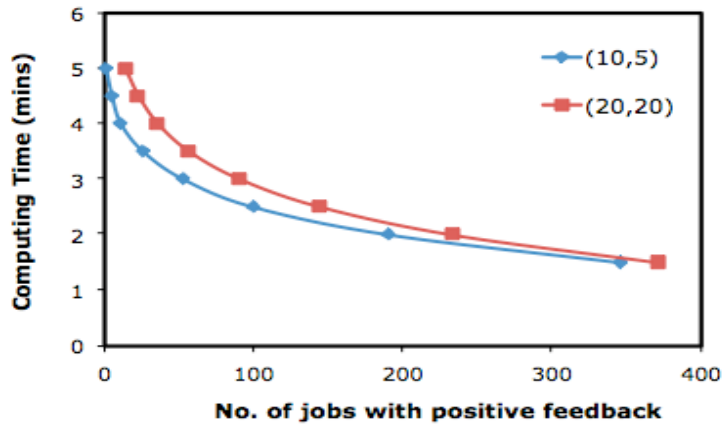
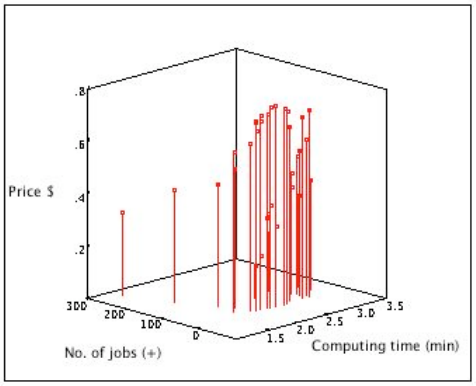


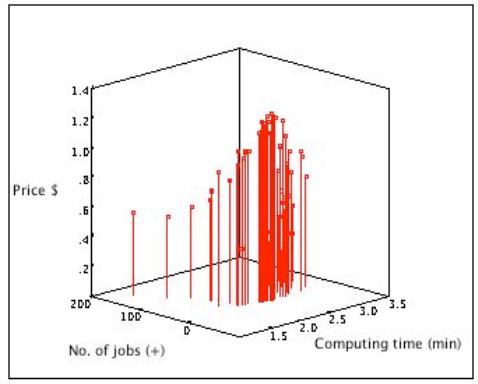
Figure 5.3 Demand curves based on value profiles from the GSPs' perspective as computing time (minutes) vs. number of jobs with positive feedback when *max_budget* = {10, 20} and *max_preferred_duration* = {5, 20}.

Clearly, the results both from the clients' perspective and from the GSPs' perspective indicate that when clients' constraints change, value profiles can capture clients' willingness-to-pay at different prices. This is consistent with demand theory. Therefore, we believe that a value profile can function as a proxy for a demand function.

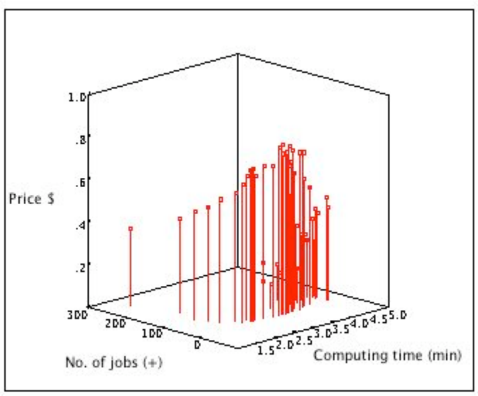
Furthermore, as prices vary based on system utilization, value profiles can be viewed as the clients' willingness-to-pay of clients at different QoSs. Figure 5.3 displays the demand curves from the GSPs' perspective, which are presented as the mean number of jobs with positive feedback at different computing times (in minutes). Undoubtedly, demand curves shift up and to the right when clients relax their constraints. As shown in Figure 5.3, at the computing time is equal to 2.5, the number of jobs with positive feedback will increase from 100 to 145 if clients increase their budget and preferred duration from (10, 5) to (20, 20). Figure 5.4 presents three-dimensional demand curves, which are presented as the mean number of jobs with positive feedback at different values of price and computing time. Clearly, the results indicate that the lower the price and the computing time, the more the client will demand. This is also consistent with the demand theory.



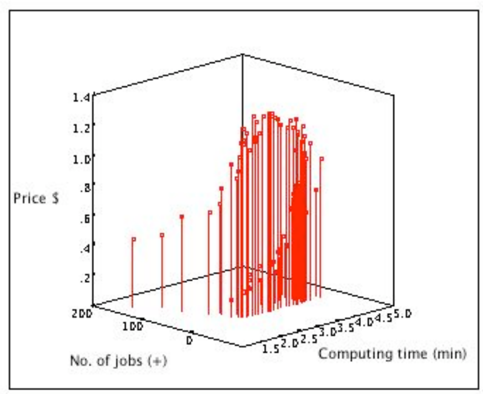
(a)



(b)



(c)



(d)

Figure 5.4 Three-dimensional demand curves based on value profiles (price vs. computing time vs. no. of jobs with positive feedback) (a) *max_budget* = {10} and *max_preferred_duration* = {5} (b) *max_budget* = {20} and *max_preferred_duration* = {5} (c) *max_budget* = {10} and *max_preferred_ duration* = {20} (d) *max_budget* = {20} and *max_preferred_duration* = {20}.

5.4. SUMMARY

In this chapter, we describe how we construct value profiles using binary feedback for a collection of heterogeneous grid clients, which GSPs can use to economically plan their resources. From the experiments, the results visibly indicate that value profiles have the shape and characteristics of demand functions. Value profiles also consist with the demand theory since they represent clients' willingness-to-pay for grid resources at different prices. Therefore, binary feedback can be used to construct value profiles, which GSPs can use as proxies for demand functions. This accepts what we hypothesize in the first research question Q1.

For the rest of this dissertation, we will use value profiles as proxies for demand functions. We believe that the use of value profiles can assists GSPs in finding an economic equilibrium point to plan their resource base.

6. ISSUES IN USING BINARY FEEDBACK FOR GRID RESOURCE PLANNING

This chapter discusses significant issues related to the use of binary feedback for grid resource planning. In reality, clients might not be truthful and cooperative. Section 6.1 determines whether clients have incentives to cooperate and to be truthful. The development of cooperation in a particular set of conditions and the development of credibility-based binary feedback model for grid resource planning are presented in Section 6.1 and Section 6.2, respectively. Next, Section 6.3 analyses GSPs' incentive to cheat and disregard unfavorable feedback. Finally, Section 6.4 investigates the effect of untruthful feedback.

6.1. CLIENTS' INCENTIVES

The objective of this section is to explore clients' incentives related to the use of binary feedback. According to Dellarocas et al. [17], feedback contributions do not directly benefit the feedback providers, while other entities benefit more directly. Thus, individuals might have a small economic incentive to provide feedback even if it is socially optimal for them to do so.

First, Section 6.1.1 demonstrates the effect of feedback contributions. Then, Section 6.1.2 studies an incentive to cooperate and how to create this incentive. Next, Section 6.1.3-Section

6.1.4 investigate trust in feedback models and explain how to promote truthful feedback, respectively.

6.1.1. The Effect of Feedback Contributions

As value profiles are based on a number of jobs with positive feedback, the probability that clients would provide feedback, *P(contribution)*, might affect the outcome of value profiles. With the low *P(contribution)*, GSPs might have less feedback information to estimate client demand. To investigate this effect, we do a sensitivity analysis of *P(contribution)* as presented in Table 6.1.

Table 6.1 Sensitivity Analysis of *P(contribution)*

	Parameters	*Values*
ENVIRONMENT	*NUM_CLIENTS*	1000
	Interarrival rate	1.0 jobs/min
	Service rate	1.0 jobs/min
CLIENT AGENTS	*Budget*	Uniform (1, 20)
	Preferred duration	Uniform (1, 15)
	No_of_Jobs	Uniform (10, 50)
	λ_j (client's QoS threshold)	Uniform (-2, 0)
	α_j	1
	$t^{retransmit}$	1000 min
	P(contribution)	{0.0, 0.2, 0.6, 1.0}
	P(untruthful)	0
GSP AGENTS	p_i	Vary based on system utilization
	a_i	0
	b_i	0.1

In this experiment, after a service, each client provides binary feedback FB_j based on the value of his/her satisfaction, which is expressed as (see Table 5.2 for the summary of notations and parameters of client agents)

$$FB_j = \begin{cases} "1" & if \quad S_j \geq 0 & with \quad P(contribution) \\ "no\ rate" & if \quad S_j \geq 0 & with \quad 1-P(contribution) \\ "0" & if \quad S_j \leq -\lambda_j & with \quad P(contribution) \\ "no\ rate" & if \quad S_j \leq -\lambda_j & with \quad 1-P(contribution) \\ "no\ rate" & if \quad -\lambda_j < S_j < 0 & \end{cases} \tag{6.1}$$

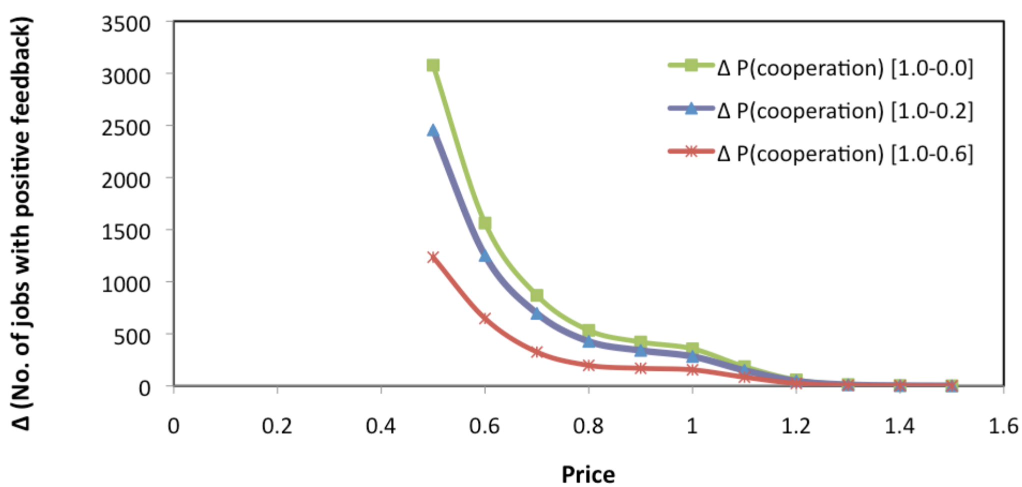


Figure 6.1 The effect of feedback contributions.

Figure 6.1 shows the result of sensitivity analysis of *P(contribution)*. The results are presented as differences in the number of jobs with positive feedback when the values of *P(contribution)* change[36]. Because of the law of demand, the big differences occur at the low

[36] For *P(contribution)*=1.0, clients will always provide feedback. For *P(contribution)*=0.6, the probability that clients will provide feedback is 0.6. For *P(contribution)*=0.2, the probability that clients will provide feedback is 0.2. For *P(contribution)*=0.0, clients will not provide any feedback.

price. Clearly, *P(contribution)* has an effect on value profiles by reducing the preciseness of demand estimation. Therefore, we have to study how to create incentives to cooperate.

6.1.2. Incentives to Cooperate

Clients do not cooperate unless they receive some benefits from their contribution. Like eBay reputation, eBayers receive benefits in their future trading. Even there, eBay persistently prompts transacting parties to leave feedback. In our study, GSPs ask clients to spend time to provide feedback after they receive a result, which can be considered as a kind of cost to them. If clients cannot clearly see benefits from their contribution, they do not have any economic incentives to cooperate with GSPs. As a result, we require a mechanism to create clients' incentive to cooperate.

We use an individual effort model to explain how to encourage feedback contributions, as presented in Figure 6.2. Clearly, people work hard when they think their effort will help them achieve outcomes that they value [31]. After providing feedback, clients will continue their contribution if they obtain noticeable benefits, which can be achieved through providing "selective incentives" and by publishing "community activity".

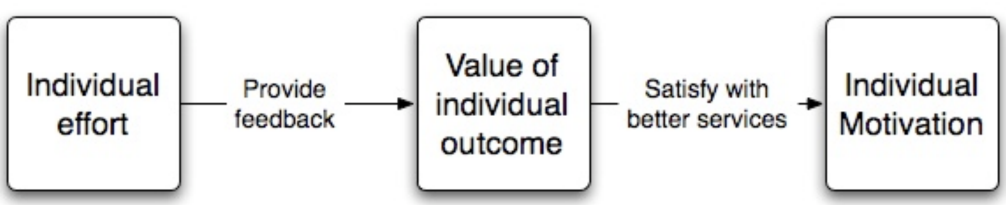


Figure 6.2 Individual effort model.

According to Olson [30],

> The incentive must be "selective" so that those who do not join the organization working for the group's interest … can be treated differently from those who do. These "selective incentives" can be either negative or positive, in that they can either coerce by punishing … or they can be positive inducements offered to those who act in the group interest… Only an organization that sold private or noncollective products, or provided social or recreational benefits to individual members, will have a source of these positive inducements.

In our case, GSPs have to treat feedback-providing clients[37] better than non-feedback-providing clients[38]. For example, in queuing, schedulers can set higher priority to feedback-providing clients. Therefore, schedulers will process jobs from feedback-providing clients before those from non-feedback-providing clients. Giving feedback-providing clients a better price can be also considered as a kind of noticeable benefits.

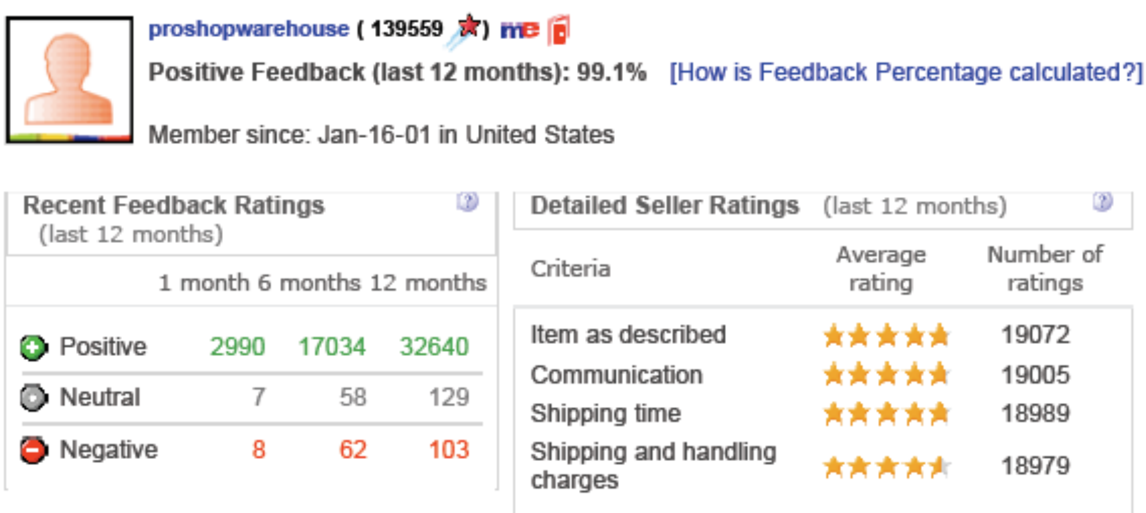


Figure 6.3 A typical eBay feedback profile, as of May 2008.

Another way to increase clients' motivation to make contributions is to show their community activities [32]. For example, like eBay, GSPs can show their feedback profiles, as

[37] Clients who provide feedback to GSPs.
[38] Clients who do not provide feedback to GSPs.

shown in Figure 6.3. The percentage of positive feedback can be calculated from the number of jobs with positive feedback divided by the total number of processed jobs. This percentage represents how the GSP manages jobs according to the SLA agreed upon by both the client and the GSP.

Therefore, GSPs can increase clients' incentives to cooperate by making sure that feedback-providing clients always receive more benefits than non-feedback-providing clients. Furthermore, by publishing GSPs' feedback profile, it prevents GSPs from over-advertising their service; as a result, it benefits future potential clients to understand the true quality of GSPs.

6.1.3. Incentives to be Truthful

Rationally, self-interested individuals want to maximize their own payoff without any concern for the other's payoff. In our case, clients prefer to consume as many resources as possible within their budgets. In a good service case, although they may already be satisfied with the current service, they may still want a better service by lying to GSPs. If GSPs believe them, they will receive an upgraded service without any extra costs. On the other hand, in a bad service case, clients can receive more benefits by lying that the service is a lot worse than it is. Accordingly, they have an economic incentive to provide untruthful feedback. We assert that a feasible way to promote honesty in feedback models is to use credibility mechanisms.

The use of credibility mechanisms enables GSPs to detect and penalize insincere or biased clients. The idea is to ensure that sincere clients always receive more benefits than insincere or biased clients. Therefore, clients will fear of punishments and will provide truthful feedback because of higher payoffs.

6.1.4. Promoting a Truthful Feedback

We have assumed that clients will decide whether to submit a job based on GSPs' service announcement subject to clients' constraints. We also have assumed that prices will be fixed after GSPs and clients have an agreement. In order to detect untruthful feedback, we have to make additional assumptions. We assume that when clients decide to submit their job, it means that they are willing to pay at that price and their preferred duration is greater than or equal to the estimated computing time ($t_j^{preferred\_duration} \geq estimated\_computing\_time$). Therefore, GSPs can use the estimated computing time as the reference of clients' preferred duration. In this dissertation, we assume that clients' preferred duration is equal to the estimated computing time ($t_j^{preferred\_duration} = estimated\_computing\_time$).

With clients' preferred duration information ($t_j^{preferred\_duration}$), GSPs can detect and penalize insincere or biased clients by comparing $t_j^{preferred\_duration}$ with their quantifiable performance record, as described in Section 4.3. The idea is that GSPs will record the total computing time ($t_j^{total\_computing}$) of each job, and then evaluate the received feedback based on the difference between $t_j^{total\_computing}$ and $t_j^{preferred\_duration}$. GSPs usually expect to receive positive feedback if they can finish jobs within preferred durations[39], and vice versa. Thus, the expected feedback ($FB_j^{\exp}$) can be expressed as

$$FB_j^{\exp} = \begin{cases} "1" & if\ t_j^{total\_computing} \leq t_j^{preferred\_duration} \\ "0" & if\ t_j^{total\_computing} > t_j^{preferred\_duration} \end{cases} \tag{6.2}$$

If the received feedback does not match to what GSPs expected ($FB_j^{expected} \neq FB_j^{received}$), that feedback is considered as untruthful feedback and will be discarded. Moreover, that client will be

[39] As discussed in Section 5.3, we assumed that an estimated service cost is the same as the final cost (%ΔC = 0).

held for some periods of time ($t_j^{penalty}$) before receiving next service and will not be allowed to provide any feedback after that service. If they are allowed to provide feedback, they will provide negative feedback because of the longer computing time ($t_j^{greedy\_computing} = t_j^{total\_computing} + t_j^{penalty}$). This might drop the percentage of positive feedback and lead to the wrong outcome. On the other hand, if the received feedback matches to the expected feedback ($FB_j^{expected} = FB_j^{received}$), that feedback will be counted. This process will continue until there are no new jobs; as a result, we believe that the use of credibility mechanism can promote truthful feedback[40]. The algorithm of this mechanism is provided in Figure 6.4.

```
Algorithm of Credibility Mechanism

After GSPs receive a client's job

    CHECK client's punishment state

    IF pun_state = false THEN
        PROCESS  the job
    ELSE
        HOLD the job for penalty time
    END IF

After GSPs receive client's feedback

    CHECK whether the received feedback is reliable
            by comparing to what GSPs expected

    IF FBj(received) = FBj(expected) THEN
        COUNT  the truthful feedback
    ELSE
        DISCARD the untruthful feedback
        PENALIZE the client
    END IF
```

Figure 6.4 Algorithm of credibility mechanism [26].

[40] See Credibility-based feedback games in Section 6.2.4.

6.2. ANALYSIS OF CLIENTS' INCENTIVES

Given clients' incentives in Section 6.1, this section presents analysis results using game theory. First, Section 6.2.1 defines a payoff of an individual player. Then, Section 6.2.2 analyzes quality choice games in different pricing scenarios to explain why clients' feedback plays an important role in grid resource planning. Then, Section 6.2.3 analyzes feedback games to study the cooperation between GSP vs. client and client vs. client. Finally, Section 6.2.4 determines whether the use of credibility mechanisms can help the cooperation to emerge.

6.2.1. Individual Payoff

Before starting game analyses, we have to define a payoff of each individual player. Two key players are a GSP and a client. The profit (payoff) for a GSP is known as

$$P = R - C \tag{6.3}$$

where R is revenues from providing a service to a client, and C is costs of providing that service. We assume that a GSP always sets its revenues to cover its costs ($R > C > 0$).

The payoff for a client is defined as

$$P = Q - R \tag{6.4}$$

where R is the service cost that the client has to pay, which is equivalent to the revenue R of the GSP. Q is the client's perceived value, which decays exponentially with time; this represents the QoS that the client received from the GSP. Therefore, in this function, the value of Q is proportional to the difference between preferred duration and total computing time, which we express as

$$Q = Re^{(t^{preferred\_duration} - t^{total\_computing})} \tag{6.5}$$

For each strategic combination, a payoff of each player is calculated from the difference between his/her payoff before making a decision and that after making such decision, which we express as

$$\begin{aligned} P_{GSP} &= \Delta R - \Delta C \\ P_{client} &= \Delta Q - \Delta R \end{aligned} \tag{6.6}$$

For the following games, these payoffs mainly depend on specified step-level parameters when upgrading or downgrading a service in each case.

6.2.2. Quality Choice Games without Feedback Information

The objectives of quality choice games are to illustrate how GSPs and clients cooperate without any feedback and to justify why value profiles are necessary for optimal resource planning. These games are sequential move games with perfect information, following Turocy and Stengel [21].

6.2.2.1. Game Setup

Suppose player I is a GSP and player II is an existing client. The GSP makes the first move, choosing between two levels of service: *Upgrade (U)* or *Downgrade (D)*. Upgrading a service requires further investments (higher costs), and these costs are independent of whether the client continues that service or not. Downgrading a service can reduce the GSP's costs.

Table 6.2 Pricing Scenarios.

Strategy	*Description*
Flat	Whether the GSP upgrades or downgrades the service, the price is still the same.
Fair	After upgrading the service, the price increases to cover the upgrade costs. After downgrading the service, the price decreases since the GSP reduces its costs.
Selfish	After upgrading the service, the price increases more than covering the upgrade costs. After downgrading the service, the price does not decrease even though the GSP reduces its costs.

Then, the client is informed about the GSP's choice and has to decide whether to *Continue* or to *Discontinue* that service. Consequently, these games have four strategic combinations: *(Upgrade,* and then *Continue)*, *(Upgrade,* and then *Discontinue)*, *(Downgrade,* and then *Continue)*, and *(Downgrade,* and then *Discontinue)*. Table 6.2 presents three pricing scenarios used to explore these games.

6.2.2.2. Case I: GSP vs. Client with Flat Pricing

In this scenario, whether the GSP upgrades or downgrades the service, the price is still the same. Table 6.3 summarizes how parameters in this quality choice game change. Figure 6.5 and Table 6.4 present this game model and its strategic form, respectively.

Table 6.3 Quality Choice Game Parameters in Case I, where $0 < \omega < 1$.

	Upgrade	*Downgrade*
Quality	$Q = (1+\omega)*Q$	$Q = (1-\omega)*Q$
Revenue	$R = R$	$R = R$
Cost	$C = (1+\omega)*C$	$C = (1-\omega)*C$

In Figure 6.5, if the GSP has chosen to upgrade the service, then the client prefers to continue, since the resulting payoff of ωQ is larger than $-Q+R$ when discontinuing. If the GSP has chosen to downgrade the service, then the client decides to either continue or discontinue based on the value of ω. First equilibrium, if the GSP slightly downgrades the service (small value of ω), then the client prefers to continue since the resulting payoff of $-\omega Q$ is larger than ($-Q+R$) when discontinuing. In this case, the GSP prefers to downgrade the service, which results in the payoff of ωC, to upgrade, which leads to the payoff of $-\omega C$.

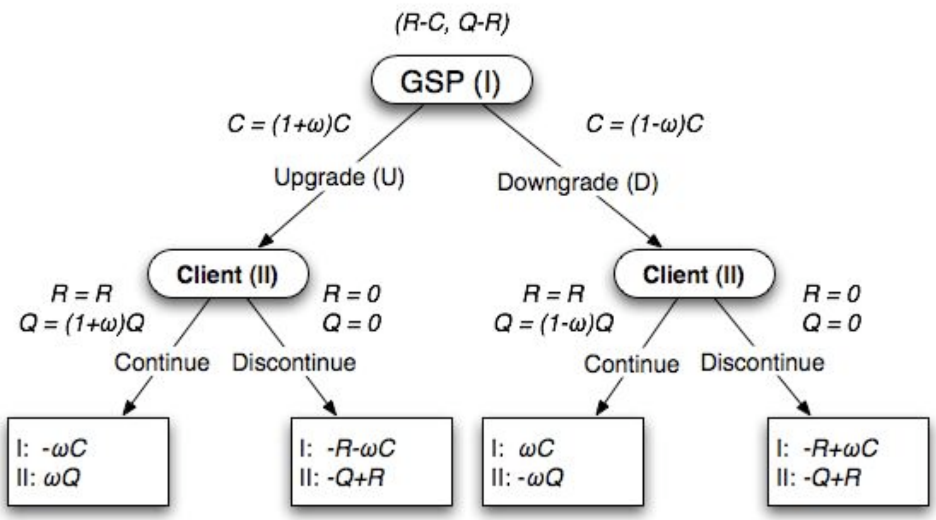


Figure 6.5 Quality choice game between GSP and client in Case I, where $Q>R>C>0$ and $0<\omega<1$.

Table 6.4 Strategic Form of Quality Choice Game in Case I, where $Q>R>C>0$ and $0<\omega<1$.

II (Client) / *I (GSP)*	*U: Cont'* *D: Cont'*	*U: Cont'* *D: Discont'*	*U: Discont'* *D: Cont'*	*U: Discont'* *D: Discont'*
Upgrade (U)	ωQ $-\omega C$	ωQ $-\omega C$	$-Q+R$ $-R-\omega C$	$-Q+R$ $-R-\omega C$
Downgrade (D)	$-\omega Q$ ωC	$-Q+R$ $-R+\omega C$	$-\omega Q$ ωC	$-Q+R$ $-R+\omega C$

Second equilibrium, if the GSP downgrades the service too much (large value of ω), then the client prefers to discontinue, since the resulting payoff of $-Q+R$ becomes larger than $-\omega Q$ when continuing. In this case, the GSP prefers to downgrade the service, which results in the payoff of $–R+\omega C$, to upgrade, which leads to the payoff of $-\omega C$. However, the GSP might also prefer to upgrade the service, since the payoff of $-\omega C$ might be larger than $–R+\omega C$ when downgrading, as shown in Table 6.4. As a result, the shaded areas in Table 6.4 represent three possible Nash equilibria: (*Upgrade, Continue*), (*Downgrade, Continue*), and (*Downgrade*, *Discontinue*). The detail of each strategic combination is described in Table 6.5.

Table 6.5 Payoff Matrix Detail for Case I.

Choice Combination	*GSP*	*Client*
GSP: Upgrade Client: Continue	Although, the service price does not cover the upgrade costs, the GSP still earns its revenues. This decision decreases GSP's benefit.	The client is very happy because he/she receives a better service without additional costs. The client gains a lot of benefits from this decision.
GSP: Upgrade Client: Discontinue	Not only the GSP loses money in upgrading the service, but also loses the client. This decision is not effective.	The client just wants to discontinue the service although he/she can receive a better service. He/she is not satisfied with the service. There is no benefit from this decision.
GSP: Downgrade Client: Continue	The GSP succeeds at reducing its costs while still keeping the existing client. So, the GSP gains benefit from this decision.	Although the QoS is lower, the client is still satisfied with it. This decision decreases client's benefit since the client still has to pay the same price.
GSP: Downgrade Client: Discontinue	Although the GSP can reduce its costs, the GSP loses the existing client. This decision is not effective.	The client is not willing to pay the same price to receive a lower QoS. There is no benefit from this decision.

6.2.2.3. Case II: GSP vs. Client with Fair Pricing

In this case, after upgrading the service, the price increases to cover the upgrade costs. On the other hand, after downgrading the service, the price decreases since the GSP can save its costs. Table 6.6 summarizes how parameters in this quality choice game change. Figure 6.6 and Table 6.7 present this game model and its strategic form, respectively.

Table 6.6 Quality Choice Game Parameters in Case II, where $0 < \omega < 1$.

	Upgrade	*Downgrade*
Quality	$Q = (1+\omega)*Q$	$Q = (1-\omega)*Q$
Revenue	$R = (1+\omega)*R$	$R =(1-\omega)*R$
Cost	$C = (1+\omega)*C$	$C = (1-\omega)*C$

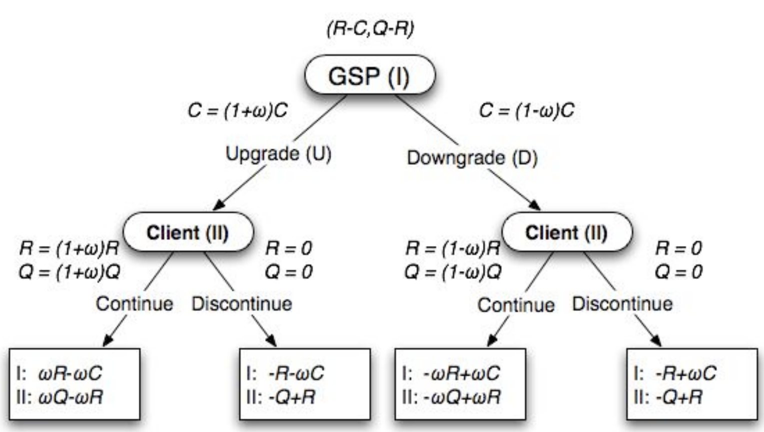


Figure 6.6 Quality choice game between GSP and client in Case II, where $Q>R>C>0$ and $0<\omega<1$.

Table 6.7 Strategic Form of Quality Choice Game in Case II, where $Q>R>C>0$ and $0<\omega<1$.

II (Client) / *I (GSP)*	*U: Cont'* *D: Cont'*	*U: Cont'* *D: Discont'*	*U: Discont'* *D: Cont'*	*U: Discont'* *D: Discont'*
Upgrade (U)	$\omega Q- \omega R$ $\omega R-\omega C$	$\omega Q- \omega R$ $\omega R-\omega C$	$-Q+R$ $-R-\omega C$	$-Q+R$ $-R-\omega C$
Downgrade (D)	$-\omega Q+\omega R$ $-\omega R+\omega C$	$-Q+R$ $-R+\omega C$	$-\omega Q+\omega R$ $-\omega R+\omega C$	$-Q+R$ $-R+\omega C$

In Figure 6.6, first equilibrium, if the GSP has chosen to upgrade the service, then the client prefers to continue, since the resulting payoff of ωQ-ωR is larger than $-Q+R$ when discontinuing. If the GSP has chosen to downgrade the service, then the client prefers to continue, since the resulting payoff of $-\omega Q+\omega R$ is larger than $-Q+R$ when discontinuing. In this case, the GSP prefers to upgrade the service, which results in the payoff of ωR-ωC, to downgrade, which leads to the payoff of $-\omega R+\omega C$.

Table 6.8 Payoff Matrix Detail for Case II.

Choice Combination	*GSP*	*Client*
GSP: Upgrade Client: Continue	The GSP increases the service price to cover the upgrade costs, and the client can afford it. So, the GSP still gains benefit.	The client is willing to pay additional costs to receive a better service. The client still gains benefit from this decision.
GSP: Upgrade Client: Discontinue	Not only the GSP loses money in upgrading the service, but also loses the client. This decision is not effective.	The client does not want to pay additional costs even though he/she can receive a better service. There is no benefit from this decision.
GSP: Downgrade Client: Continue	The GSP reduces the service price to keep the existing client. This decision decreases GSP's benefit.	The client is satisfied with a lower service and price. This decision decreases client's benefit.
GSP: Downgrade Client: Discontinue	Although the service price decreases, the GSP still loses the existing client. This decision is not effective.	The client is not satisfied to with a lower QoS although the price is cheaper. There is no benefit from this decision.

In Table 6.7, the (*Downgrade; U: Discon't, D: Con't*) cell is also the equilibrium but it is not the optimal choice. The shaded areas in Table 6.7 represent two Nash equilibria: (*Upgrade, Continue*) and (*Downgrade, Continue*). The detail of each strategic combination is presented in Table 6.8.

6.2.2.4. Case III: GSP vs. Client with Selfish Pricing

In this case, after upgrading the service, the price increases more than covering the upgrade costs. On the other hand, after downgrading the service, the price does not decrease even though the GSP can save its costs. Table 6.9 summarizes how parameters in this quality choice game change. Figure 6.7 and Table 6.10 present this game model and its strategic form, respectively.

Table 6.9 Quality Choice Game Parameters in Case III, where $0 < \omega < k < 1$.

	Upgrade	*Downgrade*
Quality	$Q = (1+\omega)*Q$	$Q = (1-\omega)*Q$
Revenue	$R = (1+k)*R$	$R = R$
Cost	$C = (1+\omega)*C$	$C = (1-\omega)*C$

In Figure 6.7, if the GSP has chosen to upgrade the service, then the client decides to either continue or discontinue based on the values of ω and k. The client prefers to continue if the resulting payoff of $\omega Q-kR$ is larger than $-Q+R$ when discontinuing, and vice versa.

If the GSP has chosen to downgrade the service, then the client decides to either continue or discontinue based on the value of ω. The client prefers to continue if the resulting payoff of $-\omega Q$ is larger than $-Q+R$ when discontinuing, and vice versa.

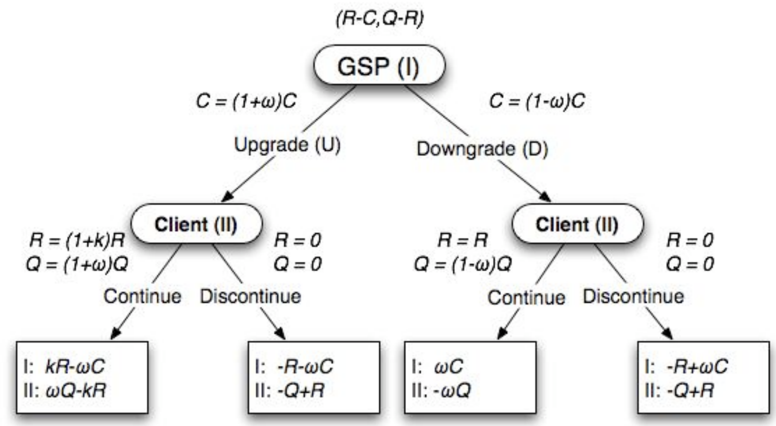


Figure 6.7 Quality choice game between GSP and client in Case III, where $Q>R>C>0$ and $0<\omega<k<1$.

Table 6.10 Strategic Form of Quality Choice Game in Case III, where $Q>R>C>0$ and $0<\omega<k<1$.

II (Client) *I (GSP)*	*U: Cont'* *D: Cont'*	*U: Cont'* *D: Discont'*	*U: Discont'* *D: Cont'*	*U: Discont'* *D: Discont'*
Upgrade (U)	ωQ-kR kR-ωC	ωQ-kR kR-ωC	-Q+R -R-ωC	-Q+R -R-ωC
Downgrade (D)	-ωQ ωC	-Q+R -R+ωC	-ωQ ωC	-Q+R -R+ωC

First equilibrium, if the payoff of ωQ-kR is larger than -Q+R, then the GSP prefers to upgrade the service, which results in the payoff of kR-ωC. Second equilibrium, if the payoff of ωQ-kR is less than -Q+R and if the payoff of -ωQ is larger than -Q+R, then the GSP prefers to downgrade the service, which results in the payoff of ωC. Third equilibrium, if the payoff of ωQ-kR is less than -Q+R and if the payoff of -ωQ is less than -Q+R, then the GSP still prefers to downgrade the service, which results in the payoff of –R+ωC. As a result, the shaded areas in

Table 6.10 represent three possible Nash equilibria: (*Upgrade, Continue*), (*Downgrade, Continue*), and (*Downgrade, Discontinue*). The detail of each strategic combination is described in Table 6.11.

Table 6.11 Payoff Matrix Detail for Case III.

Choice Combination	*GSP*	*Client*
GSP: Upgrade Client: Continue	The GSP gains benefit from this decision since the GSP increases price more than the upgrade costs.	The client is willing to pay high price to receive a better service. This decision decreases client's benefit.
GSP: Upgrade Client: Discontinue	Not only the GSP loses money in upgrading the service, but also loses the client. This decision is not effective.	The client does not want to pay high price. He/She is not satisfied with it. There is no benefit from this decision.
GSP: Downgrade Client: Continue	The GSP succeeds at reducing its costs while still earning the same revenues. So, the GSP gains benefit from this decision.	Although the QoS is lower, the client is still satisfied with it. This decision decreases client's benefit since the client has to pay the same price.
GSP: Downgrade Client: Discontinue	Although the GSP can reduce its costs, the GSP loses the existing client. The GSP is too greedy. So, this decision is not effective.	The client is not willing to pay the same price to receive a lower QoS. There is no benefit from this decision.

6.2.2.5. Summary of Quality Choice Games

Figure 6.8 presents the summary of quality choice games in three pricing scenarios. The results show that there are no dominant strategies. In each case, there are up to three possible Nash equilibria, as presented in Table 6.12. Clearly, the equilibria depend on the value of Q and step-level parameters (ω and *k*). The client gains different benefits from deciding to continue or discontinue, or even indifference between those two choices. This definitely affects the GSP who moves earlier. As a result, the GSP has to know how the client rates its service (Q). By obtaining the value of Q (or value profiles), the GSP can control the value of step-level parameters to improve its profit. In a word, value profiles can help GSPs to optimally plan their resources.

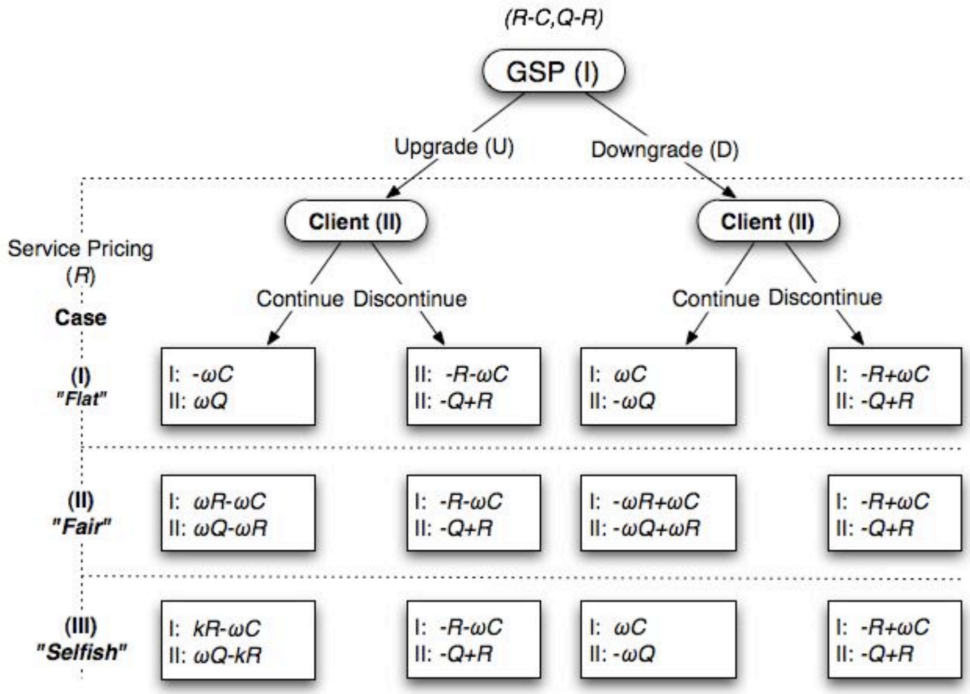


Figure 6.8 Summary of quality choice games without client's feedback, where the GSP commits to upgrade or downgrade, and the client can react accordingly.

Table 6.12 Summary of Nash Equilibria in each Pricing Scenario.

Pricing Scenario	*No. of Equilibria*	*Nash Equilibria*
Flat	3	(Upgrade, Continue), (Downgrade, Continue), and (Downgrade, Discontinue)
Fair	2	(Upgrade, Continue) and (Downgrade, Continue)
Selfish	3	(Upgrade, Continue), (Downgrade, Continue), and (Downgrade, Discontinue)

6.2.3. Feedback Games

6.2.3.1. Game Setup

Table 6.13 Feedback Game Parameters, where $0 < \omega < k < 1$.

	Upgrade *(when a client receives a poor service)*	*Downgrade* *(when a client receives a very good service)*
Q	$Q = (1+\omega)*Q$	$Q = (1-\omega)*Q$
R	$R = (1+k)*R$	$R = R$
C	$C = (1+\omega)*C$	$C = (1-\omega)*C$

According to the second research question Q2, we play non-cooperative games to study the cooperation (1) for *GSP vs. client* and (2) for *client vs. client*. In these games, we assume that all players are rational and selfish and clients always provide feedback. Then, we assume that the GSP plans resources based on the received feedback. We also assume that the GSP will upgrade a service if the percentage of received positive feedback is lower than its preferred level (upgrade trigger), and vice versa. Table 6.13 summarizes parameters used in these feedback games.

In the GSP vs. client game, we suppose that player I is a GSP and player II is a client. The GSP has two resource planning strategies after receiving the client's feedback: *Trust* or *Don't trust* the feedback. Believing the feedback might result in services that are more costly to provision. The client also has to choose between providing *Truthful* and *Untruthful* feedback. The untruthful feedback gives an insincere client more benefits than truthful feedback. On the other hand, truthful feedback is more valuable than untruthful feedback to the GSP. A resource manager will disregard the client's feedback if he/she knew that the client lied. As a result, this game has four strategic combinations: *(Trust, Truthful)*, *(Trust, Untruthful)*, *(Don't trust, Truthful)*, and *(Don't trust, Untruthful)*.

Table 6.14 Payoff Matrix of Feedback Game in Case IV.

Strategic combination	*GSP*	*Client*
GSP: Trust Client: Truthful	The GSP plans resources according to the received feedback information. This helps to eliminate ideal resources.	The client still receives a satisfactory service.
GSP: Trust Client: Untruthful	The GSP has to plan unnecessary resources. So, the GSP loses.	The insincere client can consume more resources. The client's benefit increases.
GSP: Don't trust Client: Truthful	The GSP thinks that the client lied, so the GSP decides to disregard the feedback information. There is no benefit.	The client's feedback information is overlooked. There is no benefit.
GSP: Don't trust Client: Untruthful	The GSP thinks that the client lied, so the GSP decides to disregard the feedback information. There is no benefit.	The insincere client cannot trick the GSP. There is no benefit.

In the client vs. client game, we assume that both clients do not know each other, and cannot communicate with each other. We also assume that clients do not have any knowledge about the another's move. In this game, there are four strategic combinations: (*Truthful*, *Truthful*), (*Truthful*, *Untruthful*), (*Untruthful*, *Truthful*), and (*Untruthful*, *Untruthful*).

6.2.3.2. Case IV: GSP vs. Client

In this case, we analyze the feedback game between a GSP and a client. Table 6.14 presents the detail of each strategic combination. Table 6.15 analyzes the game given that the client already receives a very good service. On other hand, Table 6.16 analyzes the game given that the client receives a poor service.

Table 6.15 Feedback game between GSP (I) and client (II) in case IV, given that the client already receives a very good service and the GSP prefers to downgrade the service.

II (Client) / *I (GSP)*	*Truthful*	*Untruthful*
Trust	$-\omega Q$ ωC	ωQ-kR kR- ωC
Don't trust	0 0	0 0

Table 6.16 Feedback game between GSP (I) and client (II) in case IV, given that the client receives a poor service and the GSP prefers to upgrade the service.

II (Client) / *I (GSP)*	*Truthful*	*Untruthful (badly poor, b>k>ω)*
Trust	ωQ-kR kR- ωC	bQ-kR kR-bC
Don't trust	0 0	0 0

In Table 6.15-Table 6.16, "Trust" strategy dominates "Don't trust" strategy. Since both players are rational, the client realizes that the GSP always prefers to trust the received feedback. Then, the client will provide untruthful feedback because of the higher payoff. As a result, the rationality of both players leads to the conclusion that the client will provide untruthful feedback and the GSP will trust it. At this point, the cooperation cannot emerge and the GSP requires a mechanism to detect the insincere client.

6.2.3.3. Case V: Client vs. Client

In this case, we analyze the feedback game between a client and a client. Table 6.17 presents the detail of each strategic combination. Table 6.18 analyzes the game given that they already receive a good service. On other hand, Table 6.19 analyzes the game given that they already receive a poor service.

Table 6.17 Payoff Matrix of Feedback Game in Case V.

Strategic combination	*Clients*
Client (I) : Truthful Client (II): Truthful	The aggregate feedback is helpful for the GSP, so the GSP gains more benefit than clients.
Client (I) : Truthful Client (II): Untruthful	The aggregate feedback is not strong.
Client (I) : Untruthful Client (II): Truthful	The aggregate feedback is not strong.
Client (I) : Untruthful Client (II): Untruthful	The aggregate feedback is beneficial for clients.

Table 6.18 Feedback game between client (I) and client (II) in case V, given that they already receive a very good service and the GSP prefers to downgrade the service.

II (Client) *I (Client)*	*Truthful*	*Untruthful*
Truthful	$-\omega Q$ $-\omega Q$	0 0
Untruthful	0 0	ωQ-kR ωQ-kR

Table 6.19 Feedback game between client (I) and client (II) in case V, given that they receive a poor service and the GSP prefers to upgrade the service.

II (Client) *I (Client)*	*Truthful*	*Untruthful* *(badly poor, $b>k>\omega$)*
Truthful	ωQ-kR ωQ-kR	0 0
Untruthful	0 0	bQ-kR bQ-kR

In Table 6.18, “Untruthful” strategy dominates “Truthful” strategy. Both clients provide untruthful feedback because of the higher payoff. In Table 6.19, it is a coordination game [50], which all Nash equilibriums exist when both players choose the same strategies. The (untruthful, untruthful) payoff Pareto dominates the (truthful, truthful) payoff. As a result, the rationality of both players leads to the conclusion that the client will provide untruthful feedback. The cooperation also cannot emerge at this point.

6.2.4. Credibility-based Feedback Games

6.2.4.1. Game Setup

What makes it possible for the cooperation to emerge is that both players have to meet each other again, recognize each other from the past transaction, and recall how other has behaved last time [29]. The decision of players not only affects the outcome of this current move, but also influences the future decision of the players. This is called an iterated game.

Using the credibility mechanism, the GSP checks whether the received feedback is truthful by comparing that with their performance record. This mechanism also allows the GSP to punish the insincere client for previous non-cooperative play. This is similar to “Tit for tat” strategy[41] in game theory. Then, the cooperation might arise as an equilibrium outcome. The incentive for client to defect is overcome by the threat of punishment, which is leading to the possibility of a cooperative outcome. Consequently, we apply the credibility mechanism into feedback games.

[41] Tit for tat is a highly effective strategy using in the iterated prisoner’s dilemma. A player using this strategy will initially cooperate, and then respond based on another player’s previous decision.

6.2.4.2. Case VI: GSP vs. Client

In this case, we analyze the credibility-based feedback game between a GSP and a client. Table 6.20 presents the detail of each strategic combination. Table 6.21 analyzes the game given that the client already receives a very good service. On other hand, Table 6.22 analyzes the game given that the client receives a poor service.

Table 6.20 Payoff Matrix of Credibility-based Feedback Game in Case VI.

Strategic combination	*GSP*	*Client*
GSP: Trust Client: Truthful	The GSP plans resources efficiently. This helps to eliminate ideal resources.	The client still receives a satisfactory service.
GSP: Trust Client: Untruthful	The GSP detects the untruthful feedback, and discards it.	The insincere client is detected and penalized for some periods of time.
GSP: Don't trust Client: Truthful	The GSP thinks that the client lied, so the GSP decides to disregard the feedback information. There is no benefit.	The client's feedback information is overlooked. There is no benefit.
GSP: Don't trust Client: Untruthful	The GSP thinks that the client lied, so the GSP decides to disregard the feedback information. There is no benefit.	The insincere client is detected and penalized for some periods of time.

Table 6.21 Credibility-based feedback game between GSP (I) and client (II) in case VI, given that the client already receives a very good service and the GSP prefers to downgrade the service.

II (Client) / *I (GSP)*	*Truthful*	*Untruthful*
Trust	$-\omega Q$ ωC	$-Q$ 0
Don't trust	0 0	$-Q$ 0

Table 6.22 Credibility-based feedback game between GSP (I) and client (II) in case VI, given that the client receives a poor service and the GSP prefers to upgrade the service.

II (Client) / *I (GSP)*	*Truthful*	*Untruthful*
Trust	ωQ-kR kR- ωC	−Q 0
Don't trust	0 0	−Q 0

In Table 6.21-Table 6.22, "Truthful" strategy dominates "Untruthful" strategy because of the credibility mechanism. Since both players are rational, the GSP realizes that the client is afraid of the punishment. Then, the client will provide truthful feedback. As a result, the rationality of both players leads to the conclusion that the client will provide truthful feedback and the GSP will trust it. The cooperation succeeds at this point.

6.2.4.3. Case VII: Client vs. Client

In this case, we analyze the credibility-based feedback game between a client and a client. Table 6.23 presents the detail of each strategic combination. Table 6.24 analyzes the game given that they already receive a good service. On other hand, Table 6.25 analyzes the game given that they receive a poor service.

In Table 6.24-Table 6.25, "Truthful" strategy dominates "Untruthful" strategy because of the credibility mechanism. As a result, the rationality of both players leads to the conclusion that clients will provide truthful feedback since the (truthful, truthful) outcome yields the highest benefit to both clients. The cooperation emerges at this point.

Table 6.23 Payoff Matrix of Credibility-based Feedback Game in Case VII.

Strategic combination	*Clients*
Client (I) : Truthful Client (II): Truthful	The aggregate feedback is helpful for the GSP, so the GSP gains more benefit than clients.
Client (I) : Truthful Client (II): Untruthful	The aggregate feedback is not strong. The insincere client is penalized.
Client (I) : Untruthful Client (II): Truthful	The aggregate feedback is not strong. The insincere client is penalized.
Client (I) : Untruthful Client (II): Untruthful	The aggregate feedback is discarded. Both clients are punished.

Table 6.24 Credibility-based feedback game between client (I) and client (II) in case VII, given that they already receive a very good service and the GSP prefers to downgrade the service.

II (Client) *I (Client)*	*Truthful*	*Untruthful*
Truthful	$-\omega Q$ $-\omega Q$	-Q 0
Untruthful	0 -Q	-Q -Q

Table 6.25 Credibility-based feedback game between client (I) and client (II) in case VII, given that they receive a poor service and the GSP prefers to upgrade the service.

II (Client) *I (Client)*	*Truthful*	*Untruthful*
Truthful	$\omega Q-kR$ $\omega Q-kR$	-Q 0
Untruthful	0 -Q	-Q -Q

6.2.5. Summary

From the quality choice games, the results clearly show that feedback information is necessary for optimal resource planning. With received feedback, GSPs can properly adjust the step-level parameters when making capital investment decisions. To do so, GSPs require feedback models to build a value profile for a collection of clients. However, the results show that the cooperation cannot emerge only through the use of feedback. Credibility mechanisms are required for cooperation to emerge. With the use of credibility mechanisms, the results show that clients will fear punishment and provide truthful feedback, and GSPs will trust it. Therefore, in this dissertation, we propose the use of credibility-based binary feedback to build value profiles, which GSPs can use to optimally plan their resources.

6.3. ANALYSIS OF GSPS' INCENTIVES

GSPs do not have an incentive to advertise or show any of their weak points [17], such as negative feedback. In Section 6.2.3, we assumed that GSPs plan their resources based on the received feedback. We also assumed that they must to upgrade their service if the percentage of received positive feedback becomes too low. Thus, they have an economic incentive to cheat by disregarding negative feedback to save these upgrade costs. In this section, we play a non-cooperative game, given that a client receives a poor service and a GSP has to upgrade the service.

Table 6.26 GSP's Incentive Game Parameters, where $0 < \omega < k < 1$.

	Upgrade
Quality	$Q = (1+\omega)*Q$
Revenue	$R = (1+k)*R$
Cost	$C = (1+\omega)*C$

In this GSP vs. client game, we suppose that player I is a GSP and player II is a client. The GSP has two strategies after receiving the client's feedback: *Cheat* or *Don't cheat*. As discussed in Section 6.1.2, we assume that the GSP's feedback profile is made public. Thus, the client has two possible strategies based on the GSP's misbehavior: *Notice* or *Don't notice*. We assume that if the client can notice that misbehavior, he/she will switch to other GSPs. As a result, this game has four strategy combinations: *(Cheat, Notice)*, *(Cheat, Don't notice)*, *(Don't cheat, Notice)*, and *(Don't cheat, Don't notice*). Table 6.26–Table 6.27 summarize parameters used in this game and detail of each strategy combination, respectively.

Table 6.27 Payoff Matrix of GSP's Incentive Game.

Strategic combination	*GSP*	*Client*
GSP: Cheat Client: Notice	The GSP disregards unfavorable feedback but the client notices it. Although the GSP can save the upgrade costs, it loses the existing client.	The client notices the misbehavior of GSP, so he/she switches to other GSPs.
GSP: Cheat Client: Don't notice	The GSP disregards unfavorable feedback and the client does not notice it. The GSP can save the upgrade costs without losing its revenues.	The client does not notice the misbehavior of GSP. The client's benefit decreases.
GSP: Don't cheat Client: Notice	The GSP plans resources based on the received feedback. This helps to keep the existing client.	The client still receives a satisfactory service.
GSP: Don't cheat Client: Don't notice	The GSP plans resources based on the received feedback. This helps to keep the existing client.	The client still receives a satisfactory service.

Table 6.28 GSP's incentive game between GSP (I) and client (II).

I (GSP) \ *II (Client)*	*Notice*	*Don't notice*
Cheat	$-Q+R$ $-R$	0 0
Don't cheat	$\omega Q-kR$ $kR-\omega C$	$\omega Q-kR$ $kR-\omega C$

Table 6.28 shows that "Don't cheat" strategy dominates "Cheat" strategy. Since the feedback profile is made public, the GSP realizes that the client can notice its misbehavior. Thus, the GSP will not cheat because of the higher payoff. As a result, the rationality of both players leads to the conclusion that the GSP will cooperate with clients.

6.4. THE EFFECT OF UNTRUTHFUL FEEDBACK

This chapter investigates the issues in using the credibility-based binary feedback model. We have explored GSPs' incentives and clients' incentives to cooperate and to be truthful. According to the game analyses, GSPs are better off not cheating by disregarding unfavorable feedback since their feedback profile is made public. Also, clients are better off cooperating with GSPs because of the use of credibility mechanism. However, the model cannot filter all untruthful feedback because of limited information received from clients. Thus, non-cooperative and untruthful clients still occur in two cases, as summarized in Table 6.29.

Table 6.29 The Effect of Untruthful Feedback.

Client Satisfaction	*Expected Feedback*	*Received Feedback*	*Analysis*	*Detection*	*Note*
(1) $S_j \geq 0$	"+"	"No rate"	Non-cooperative / Untruthful	No. This will affect value profiles and client satisfaction rates.	See Section 7.2.1.
(2) $\lambda_j \leq S_j < 0$	"No rate"	"-"	Untruthful	No. This will affect client satisfaction rates.	See Sections 7.2.2, 7.2.4, and 7.3.

In the first case, although GSPs finish jobs within preferred durations and budgets, clients might not response because of noncooperation or being untruthful. In the second case, when GSPs slightly fail to meet clients' requirement, untruthful clients will provide negative feedback instead of no response. These two cases will affect value profiles and client satisfaction rates (or percentage of positive feedback) and might cause GSPs' investment decision to change.

Table 6.30 Parameters for Sensitivity Analysis of Untruthful Feedback

	Parameters	*Values*
ENVIRONMENT	*NUM_CLIENTS*	1000
	Interarrival rate	1.0 jobs/min
	Service rate	1.0 jobs/min
CLIENT AGENTS	*Budget*	Uniform (1, 20)
	Preferred duration	Uniform (1, 15)
	No_of_Jobs	Uniform (10, 50)
	α_j	1
	$t^{retransmit}$	1000 min
GSP AGENTS	p_i	Vary based on system utilization
	a_i	0
	b_i	0.1
	$t^{penalty}$	1000 min

Thus, we perform a sensitivity analysis of untruthful feedback by varying *P(contribution)*, *P(untruthful)*, and clients' QoS threshold. Then, we record the change of percentage of positive feedback. Table 6.30-Table 6.31 summarize parameters used in this analysis and the value of factors used in this full factorial design with 50 replications, respectively.

In this experiment, after a service, each client provides binary feedback FB_j based on the value of his/her satisfaction, which is expressed as (see Table 5.2 for the summary of notations and parameters of client agents)

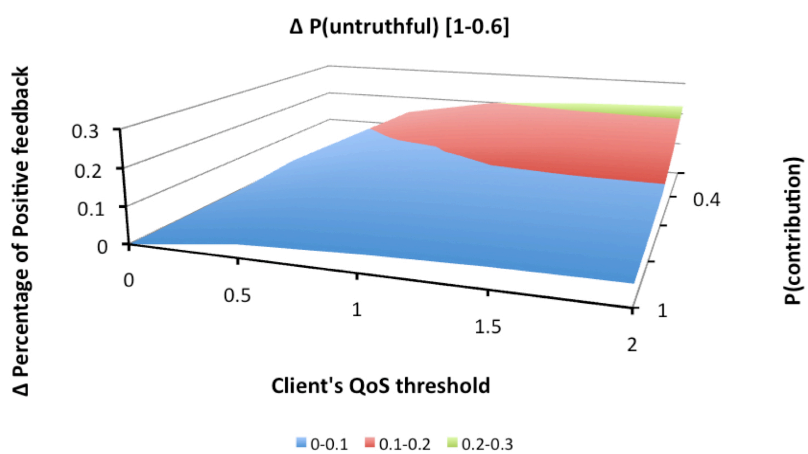
$$FB_j = \begin{cases} \text{"1"} & if \quad S_j \geq 0 & with \quad P(contribution) \\ \text{"}no\ rate\text{"} & if \quad S_j \geq 0 & with \quad 1 - P(contribution) \\ \text{"0"} & if \quad S_j \leq -\lambda_j & with \quad P(contribution) \\ \text{"}no\ rate\text{"} & if \quad S_j \leq -\lambda_j & with \quad 1 - P(contribution) \\ \text{"}no\ rate\text{"} & if \quad -\lambda_j < S_j < 0 & with \quad 1 - P(untruthful) \\ \text{"0"} & if \quad -\lambda_j < S_j < 0 & with \quad P(untruthful) \end{cases} \tag{6.7}$$

Figure 6.9 illustrates the results of sensitivity analysis of untruthful feedback. These three-dimension area graphs present the differences in percentage of positive feedback when the values of *P(untruthful)* change[42]. The results show that *P(untruthful)* affects percentage of positive feedback, which causes an accuracy of client satisfaction rate to decrease up to 24% and 32%, as shown in Figure 6.9(a) and Figure 6.9(b), respectively. In Chapter 7, we will examine whether untruthful feedback affects GSPs' investment decision.

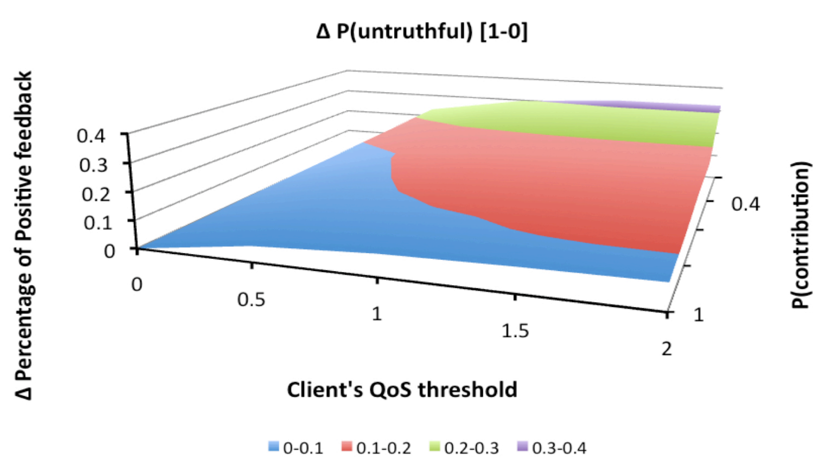
[42] When *P(untruthful)* = 0, clients will not provide any untruthful feedback. When *P(untruthful)* = 0.6, the probability that clients will provide untruthful feedback is 0.6. When *P(untruthful)* = 1, clients will always provide untruthful feedback.

Table 6.31 Full Factorial Design for Sensitivity Analysis of Untruthful Feedback

Factors	*Levels*
P (contribution)	{0.2, 0.4, 0.6, 0.8, 1.0}
P (untruthful)	{0, 0.6, 1}
Clients' QoS threshold	{0, -0.5, -1.0, -1.5, -2.0}
# of experiments	$5 \times 3 \times 5 \times 50 = 3{,}750$



(a)



(b)

Figure 6.9 The changes of percentage of positive feedback.

7. RESULTS AND DISCUSSIONS

This chapter presents the results and discussions of the use of credibility-based binary feedback model for grid resource planning according to the research questions Q4 and Q5. An economic equilibrium is required to test these questions. This equilibrium point can be determined by the intersection of cost function and market demand. Therefore, we have to construct a resource cost function and a proxy for market demand. First, Section 7.1 describes the resource cost function, the market demand proxy, and the parameter setup required in the experiments. Next, Section 7.2 discusses the benefits of value profiles on different aspects as outlined in research questions Q4-Q5. Lastly, Section 7.3-Section 7.4 discuss the limitations of the results and the model implementation, respectively.

7.1. MODEL SETUP

7.1.1. Resource Cost Function

Resource optimization requires both demand and cost information. Therefore, we have to construct a resource cost function. In this dissertation, GSPs might decide either to upgrade or to downgrade their computing capacity based on client demand. Since the lifetime of investments in computing resources is substantially longer than demand fluctuations, the long run cost must be used for the cost function.

To generate a cost function, we begin by selecting six server systems from the TPC-C Benchmark[43], as shown in Table 7.1. In this dissertation, we assume that these six server systems represent six different scales of GSPs measured by the number of processors per GSP. Then, we determine a long-run average total cost (LATC) for one year, which is the sum of short run average total cost (SATC) of each GSP. The $SATC_i$ can be calculated as

$$SATC_i = \frac{TCO_i + network\ cost_i + operation\ cost_i}{no.\ of\ \ job\ production_i} \tag{7.1}$$

where the total cost of ownership (TCO_i) is

$$TCO_i = hardware\ cost_i + storage\ cost_i + software\ cost_i \tag{7.2}$$

Table 7.1 Server Cost of Ownership[44], as of Feb. 17, 2008, Modified from TPC-C Benchmark [58].

GSP_i	*System*	*tpmC (transactions/minute)*	*3-yr Cost of Ownership*	*System Availability*
GSP_1	IBM System p5 570 4P c/s	236,271	$571,388	04/04/08
GSP_2	IBM System p 570	404,462	$1,335,739	11/26/07
GSP_3	IBM System x3950 M2	841,809	$2,817,186	04/01/08
GSP_4	NEC Express5800/1320Xf (16p/32c)	1,245,516	$4,874,853	04/30/08
GSP_5	BULL Escala PL1660R	1,616,162	$5,386,171	12/16/07
GSP_6	FUJITSU PRIMEQUEST 580 32p/64c	2,196,268	$9,413,014	04/30/08

By assuming that each job has 10^6 transactions, Table 7.2 shows the one-year cost analysis[45] of each GSP, which we calculated from Table 7.1. After running the regression model, Figure 7.1 shows the LATC curve, which can be expressed as

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[43] The TPC-C Benchmark simulates a complete computing environment where clients execute transactions against a database. The TPC-C is measured in transactions per minute (tpmC). See http://www.tpc.org.
[44] See Appendix A.

$$LATC = 3.59 + (-0.003)(no.of\ \ jobs) + (1.817 * 10^{-6})(no.of\ \ jobs)^2 \tag{7.3}$$

Table 7.2 One-Year Cost Analysis of each GSP.

GSP_i	*Service Rate (Job/Min)*	*No. of Job Production (x1000)*	*1-yr Cost of Ownership (x1000)*
GSP_1	0.24	122	\$190
GSP_2	0.40	210	\$445
GSP_3	0.84	436	\$939
GSP_4	1.25	646	\$1,625
GSP_5	1.62	838	\$1,795
GSP_6	2.20	1,139	\$3,138

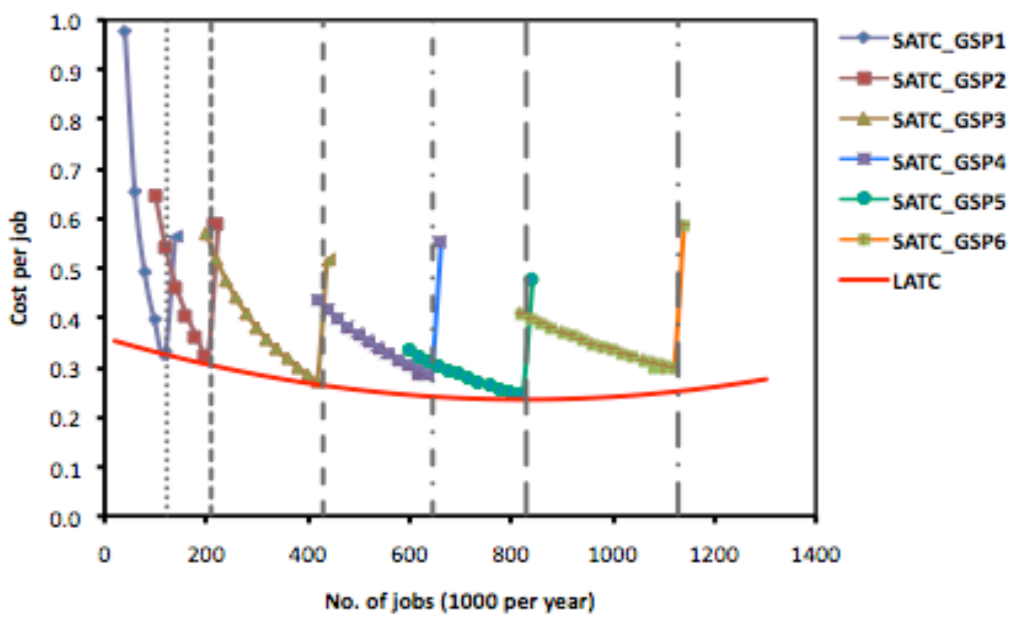


Figure 7.1 The long-run average total cost (LATC) curve of cost function, where the dashed lines are the minimum ATC of each system.

[45] As the TPC provides three-year cost of ownership analysis of each server, we simplify our cost function by dividing into one-year cost analysis.

Table 7.3 The statistical summary of Quadratic cost function.

Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.900	.811	.685	.161

The independent variable is no_of_jobs.

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	.332	2	.166	6.429	.082
Residual	.077	3	.026		
Total	.410	5			

The independent variable is no_of_jobs.

Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
no_of_jobs	-.003	.001	-3.480	-3.277	.047
no_of_jobs ** 2	1.817E-6	.000	3.015	2.840	.066
(Constant)	3.590	.197		18.227	.000

As shown in Table 7.3, the statistical summary indicates that this cost function has a high coefficient of determination (R^2=0.811) and a low significance level (Sig.=0.082). In other words, this cost function fits the data at 81.1% and the confidence interval of this cost function is 92%.

7.1.2. Market Demand

We showed earlier that a value profile could function as a proxy for a demand function of an individual GSP, so the sum of each value profile can be used as a proxy for market demand. By assuming that all value profiles are published, market demand can be expressed as[46]

$$Market\ Demand = \sum_{i=1}^{\#GSPs} \left(value\_profile_i \right) \tag{7.4}$$

[46] We will justify this concept in the next section.

In this dissertation, we use this market demand proxy to represent all grid clients' willingness-to-pay. Furthermore, as we assume that the market is a perfectly competitive market, normal profits only arise when GSP's long-run economic equilibrium is reached. Thus, with the use of value profiles, the economic equilibrium can be determined by the intersection of the proxy for market demand and the LATC.

7.1.3. Experiment Setup

In the experiments, we assume that each client always provides feedback FB_j based on the value of satisfaction level S_j that can be expressed as (see Table 5.2 for the summary of notations and parameters of client agents)

$$FB_j = \begin{cases} \text{"1"} & \text{if} \quad S_j \geq 0 \quad \text{with } P(\text{contribution}) \\ \text{"no rate"} & \text{if} \quad S_j \geq 0 \quad \text{with } (1 - P(\text{contribution})) \\ \text{"0"} & \text{if} \quad S_j \leq -\lambda_j \quad \text{with } P(\text{contribution}) \\ \text{"no rate"} & \text{if} \quad S_j \leq -\lambda_j \quad \text{with } (1 - P(\text{contribution})) \\ \text{"no rate"} & \text{if} \quad -\lambda_j < S_j < 0 \quad \text{with } (1 - P(\text{untruthful})) \\ \text{"0"} & \text{if} \quad -\lambda_j < S_j < 0 \quad \text{with } P(\text{untruthful}) \end{cases} \tag{7.5}$$

We believe that GSPs can increase clients' incentives to cooperate, as discussed in Section 6.1.2. Thus, in this dissertation, we assume that clients always provide feedback. Table 7.4 summarizes the default values of parameters for the experiments.

In this dissertation, we consider two cases: *a low demand case* and *a high demand case*. In market case I, the high-capacity GSP might want to downsize because of low demand. In market case II, the low-capacity GSP might want to upgrade because of high demand. These two cases frequently arise when making capital investment decisions. Table 7.5 presents the design of these experiments.

Table 7.4 Model Parameters

	Parameters	*Values*
ENVIRONMENT	*TIME*	518400 min (1 year)
CLIENT AGENTS	*Budget*	Uniform (5, 100)
	Preferred duration	Uniform (5, 30)
	No_of_Jobs	Uniform (10, 100)
	λ_j (QoS threshold)	Uniform (-2, 0)
	α_j	1.0
	$t^{retransmit}$	1000 min
	P(contribution)	1.0
GSP AGENTS	p_i	Vary based on system utilization
	a_i	0
	b_i	0.1
	$t^{penalty}$	1000 min

Table 7.5 Full Factorial Design for Research Questions Q4-Q5

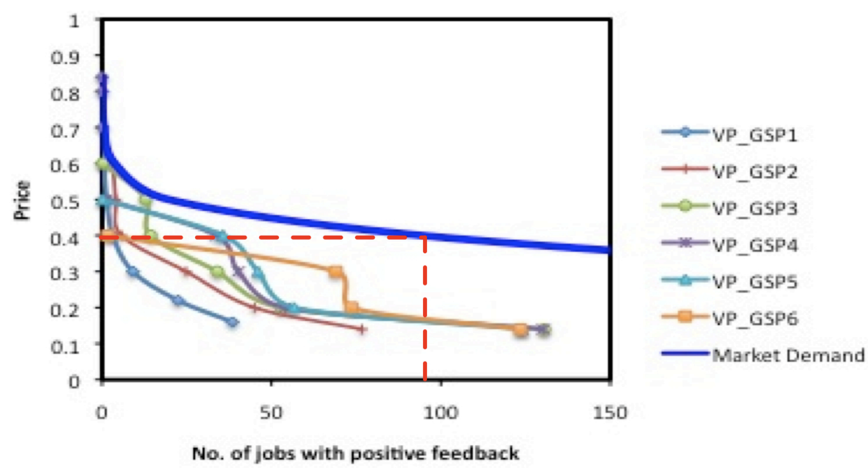
Factors	*Levels*

Job Load	• Low demand (Market Case I)
	  o NUM_CLIENTS = 5,000
	  o Interarrival rate = 0.3 job/min
	• High demand (Market Case II)
	  o NUM_CLIENTS = 50,000
	  o Interarrival rate = 0.5 job/min

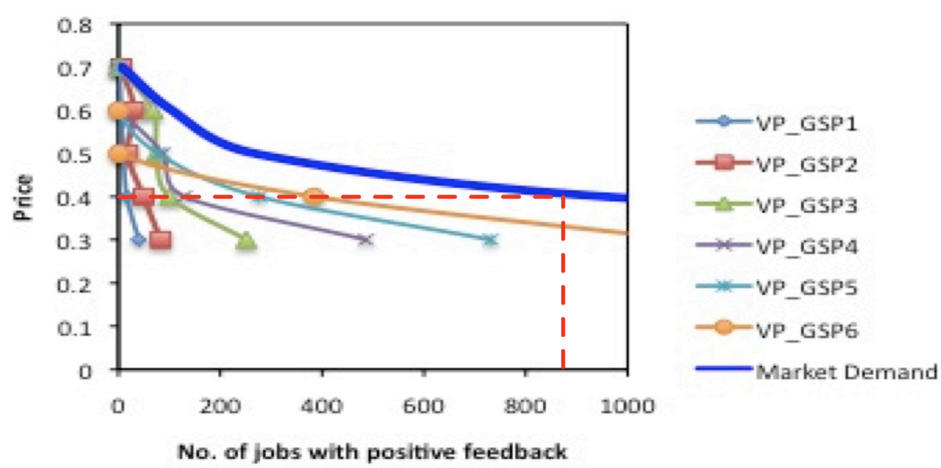
Service Rate (job/min)	{0.24, 0.40, 0.84, 1.25, 1.62, 2.20}
P (untruthful)	{0, 1.0}

Note: See Table 7.4 for other parameters.

Before starting the experiments, we have to justify the concept of market demand. From Table 7.5, Figure 7.2 presents the market demand curves calculated from the horizontal sum of value profile of each GSP in each price range. For example, in Figure 7.2(b), at the price is equal to 0.4, the sum of six value profiles is 955[47]. According to the concept of market demand in Section 7.1.2, this number can be used as a proxy for market demand at that price. In this dissertation, we will use this proxy for the market demand that represents clients' willingness-to-pay for grid resources.



(a) Market Case I



(b) Market Case II

Figure 7.2 Market demand of GSPs (a) low-demand case and (b) hi-demand case.

[47]The horizontal sum of six value profiles is 16.5+49+100+129+276.5+384 = 955.

Furthermore, we assume that when any GSP decides to change its resource base in response to market demand, other GSPs will not change their resource base. This assumption allows us to concentrate on whether the use of value profiles provides a benefit to a GSP.

7.2. BENEFITS OF VALUE PROFILES

The goal of this section is to demonstrate how value profiles benefit both GSPs and clients, which are the research questions Q4-Q5. From the GSPs' perspective, we study the effect of the use of value profiles on profit, resource usage, and percentage of positive feedback or client satisfaction rate. From the clients' perspective, we examine job success rate.

7.2.1. Case I: Low Demand with Truthful Feedback

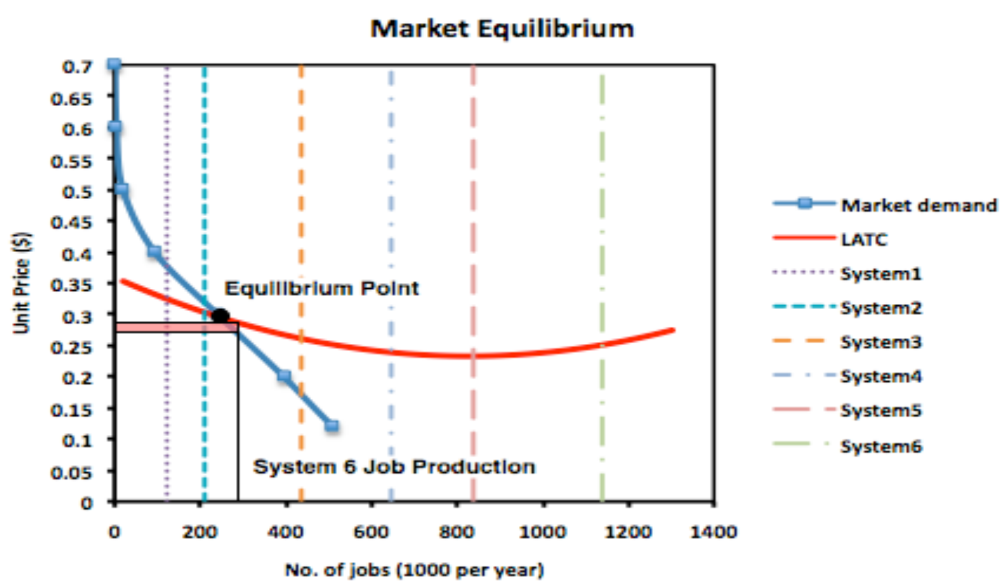


Figure 7.3 Market equilibrium in Case I, given that market demand is equal to marginal revenue.

In this case, we present the case where GSP_6 considers downgrading its computing capacity because of low demand. Without value profiles, GSP_6 produces 274,711 jobs/year and its revenue is below the LATC curve. This means that GSP_6 loses approximately \$5,494, as shown in the shaded area in Figure 7.3.

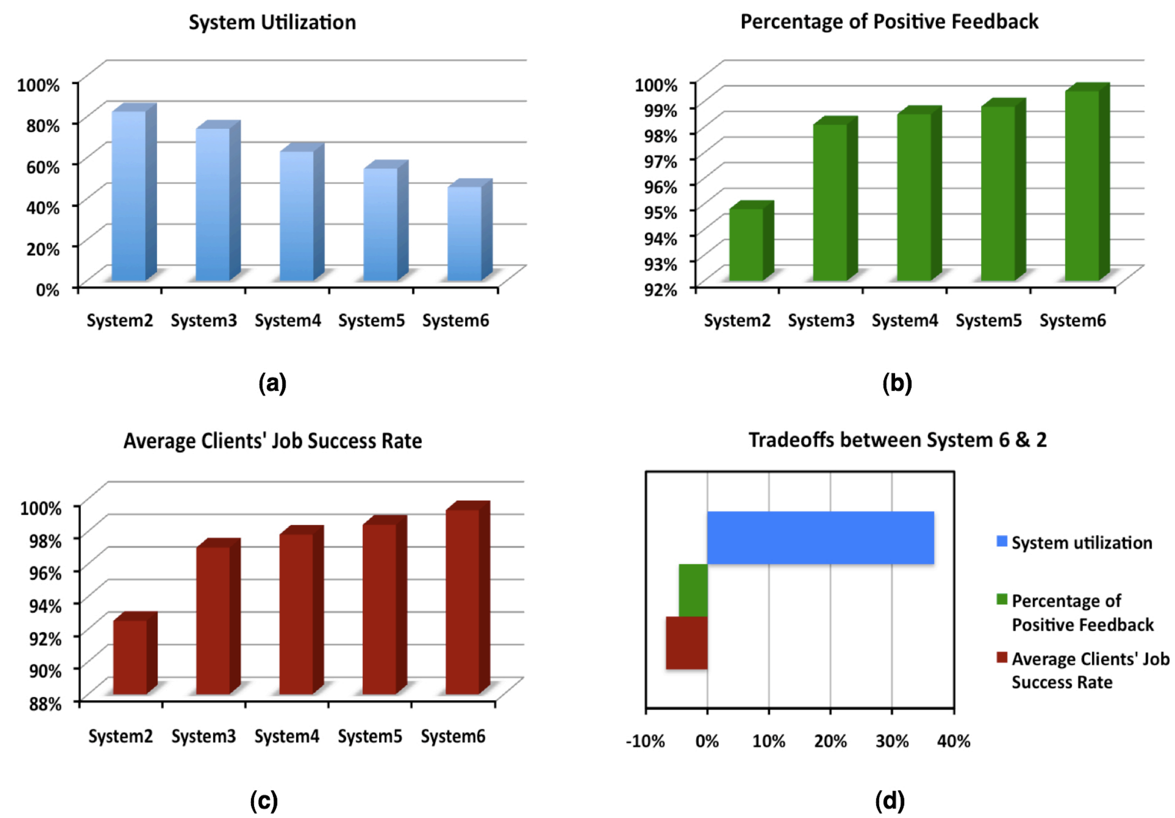


Figure 7.4 Summary of the tradeoffs when using value profiles in Case I: (a) System utilization, (b) Percentage of positive feedback, (c) Clients' job success rate, and (d) Tradeoffs when downsizing the computing capacity from system 6 to system 2.

With value profiles, as shown in Figure 7.3, GSP_6 will profit by reducing its service rate from 2.2 to 0.4 jobs/min since the equilibrium point is close to GSP_2. Figure 7.4 summarizes the tradeoffs after downgrading to the same capacity as GSP_2. The results clearly show that system utilization significantly increases from 45.7% to 82.5%. However, the percentage of positive feedback decreases from 99.4% to 94.8%. Clients' job success rate also decreases from 99.3% to 92.5%. Clearly, there are tradeoffs when using value profiles, as shown in Figure 7.4(d). While system utilization increases by 36.8% percentage points, percentage of positive feedback and clients' job success rate decreases by 4.6% and 6.8% percentage points, respectively.

Table 7.6 Paired *t*-Test on the Mean of Dependent Variables when Using Value Profiles in Case I, where Pair 1, Pair 2, and Pair 3 are the *t*_Test on $\%pos\_fb_i$, ρ_i, and $\%job_{success,\,j}$, respectively.

Paired Samples Test

		Paired Differences							
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	Sig. (2-tailed)
					Lower	Upper			
Pair 1	ppf_sys2_c1 - ppf_sys6_c1	-.045380	.077251	.010925	-.067334	-.023426	-4.154	49	.000
Pair 2	rho_sys2_c1 - rho_sys6_c1	.367880	.169282	.023940	.319771	.415989	15.367	49	.000
Pair 3	success_rate_sys2_c1 - success_rate_sys6_c1	-.067760	.111146	.015718	-.099347	-.036173	-4.311	49	.000

To conduct the statistical testing on Q4.2-Q5.1, we perform the paired *t*-test on the mean of dependent variables, which are ρ_i, $\%pos\_fb_i$,, and $\%job_{success,\,j}$. Table 7.6 presents the difference in mean performance when using value profiles. The result shows that $\rho_6^{with\_value\_profiles}$ has the significant higher mean than $\rho_6^{without\_value\_profiles}$, which is consistent with what is hypothesized in Q4.2 ($\rho_6^{with\_value\_profiles} > \rho_6^{without\_value\_profiles}$). However, the result indicates that $\%pos\_fb_6^{with\_value\_profiles}$ and $\%job_{success,6}^{with\_value\_profiles}$ have lower mean than $\%pos\_fb_6^{without\_value\_profiles}$ and $\%job_{success,6}^{without\_value\_profiles}$, respectively. These reject what are hypothesized in Q4.3-Q5.1. In summary, the use of value profiles benefits GSP_6 in resource cost saving even though client satisfaction rate decreases slightly (but still over 90%).

Since clients are worse off in this case, they might not want to cooperate with GSP_6 or even provide untruthful feedback. This will cause the market demand curve and the equilibrium point to change. To investigate this situation, we change the values of *P(contribution)* and *P(untruthful)* in Table 7.4. In this experiment, each client is assigned with different values of probabilities, as summarized in Table 7.7. Then, we observe the change of results.

Table 7.7 Changes of Model Parameters

	Parameters	*Values*
CLIENT AGENTS	*P(contribution)*	Uniform (0, 100)
	P(untruthful)	Uniform (0, 100)

Note: See Table 7.4-Table 7.5 for other parameters.

As explained in Section 6.1.4, GSPs detect untruthful feedback by comparing the received feedback with their expected feedback record. When using mechanism, GSPs expect to receive positive feedback if they can finish a job within a preferred duration[48]. Thus, this expected

[48] See Equation (6.1).

positive feedback can be used as the reference market demand curve when clients are always cooperative, *P(contribution)* = 1, and truthful, *P(untruthful)* = 0.

With non-cooperative and untruthful clients, the received market demand curve shifts down and to the left, as shown in Figure 7.5. The result shows that the received and reference equilibrium points are close to GSP_1 and GSP_2, respectively. With the received demand information, GSP_6 will downsize to the same capacity as GSP_1 instead of GSP_2. In other words, GSP_6 will reduce its service rate from 2.2 to 0.24 jobs/min, which is 1.96 jobs/min decrement. If clients are cooperative, GSP_6 will reduce the rate to 0.4 jobs/min, which is 1.8 jobs/min decrement. However, if clients are non-cooperative and untruthful, clients will experience more delays in the system, which is 0.16 jobs/min increment. In short, clients are better off cooperating with GSP_6.

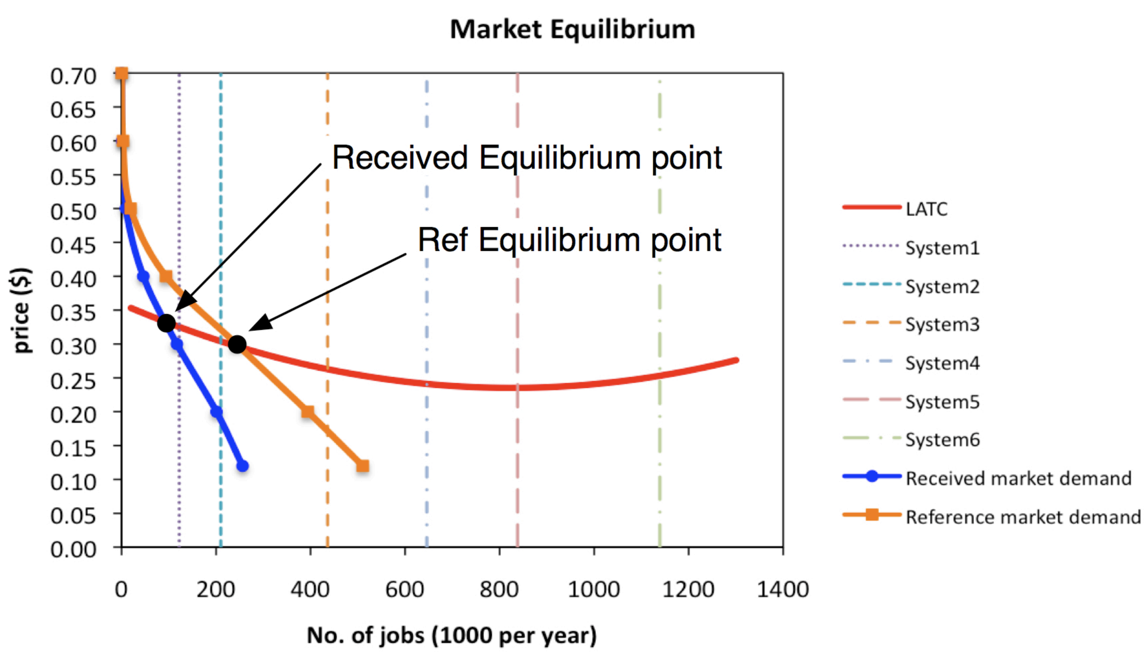


Figure 7.5 Changes of market demand curve and equilibrium point in Case I.

Furthermore, we play a non-cooperative game between GSP vs. client to investigate the development of cooperation for this situation. We suppose that player I is a GSP and player II is a client. Both players have two strategies: *Cooperate* or *Defect*. As a result, this game has four strategy combinations: *(Cooperate, Cooperate)*, *(Cooperate, Defect)*, *(Defect, Cooperate)*, and *(Defect, Defect*). Table 7.8-Table 7.9 summarize parameters used in this game and detail of each strategy combination, respectively.

Table 7.8 Client's Incentive Game Parameters, where $0 < \omega < k < 1$.

	Downgrade
Quality	$Q = (1-\omega)*Q$
Revenue	$R = R$
Cost	$C = (1-\omega)*C$

Table 7.9 Payoff Matrix of Client's Incentive Game.

Strategic combination	*GSP*	*Client*
GSP: Cooperate Client: Cooperate	The GSP can eliminate ideal resources. So, the GSP saves some costs.	The client is worse off. The client's benefit decreases but still better than defecting.
GSP: Cooperate Client: Defect	The GSP reduces its resources lower than the client demand (short supply).	Because of short supply, the client will experience high delays. So, the client's benefit decreases.
GSP: Defect Client: Cooperate	There is no benefit.	There is no benefit.
GSP: Defect Client: Defect	There is no benefit.	There is no benefit.

Table 7.10 Client's incentive game between GSP (I) and client (II).

II (Client) / *I (GSP)*	*Cooperate*	*Defect*
Cooperate	$-\omega Q$ ωC	$-kQ$ kC
Defect	0 0	0 0

From Table 7.10, the resulting payoff of *-ωQ* when cooperating is larger than *–kQ* when defecting. As a result, clients will cooperate with GSP_6 (the cooperation will emerge).

7.2.2. Case II: Low Demand with Untruthful Feedback

According to Section 6.4, untruthful feedback causes the accuracy of percentage of positive feedback to decrease. In this case, we examine whether untruthful feedback affects GSP_6's decision in case I.

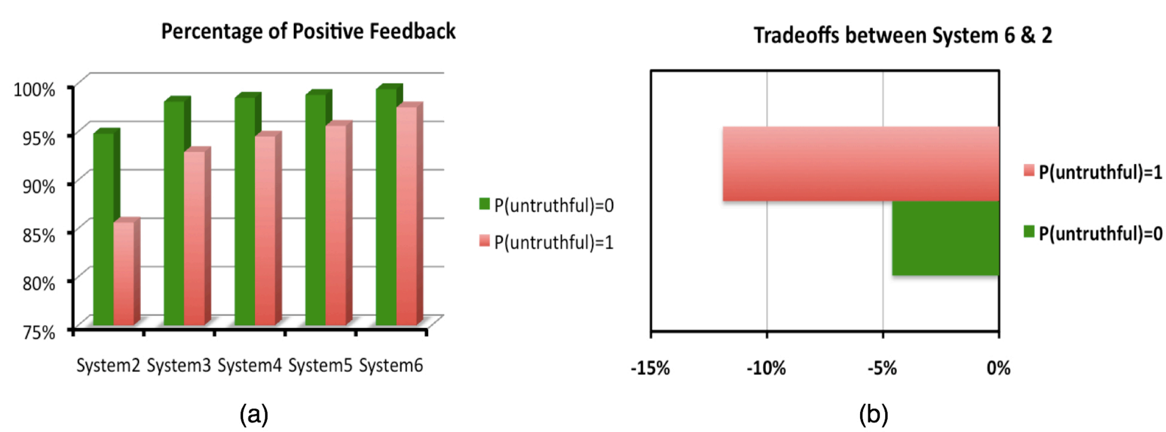


Figure 7.6 Percentage of positive feedback comparing between Case II and I.

With truthful feedback in case I, positive feedback decreases slightly by 4.6% percentage points after GSP_6 downsizes its computing capacity to the same as GSP_2. However, with untruthful feedback in this case, positive feedback decreases from 97.5% to 85.6%, which is 11.9% decrement in percentage points as presented in Figure 7.6(b). According to the statistical testing in Table 7.11, untruthful feedback reduces the accuracy of positive feedback by 7.36% percentage points.

Table 7.11 Paired *t*-Test on the Mean of Percentage of Positive Feedback Comparing between Case II and I.

Paired Samples Test

		Paired Differences		
		Mean	Std. Deviation	Std. Error Mean
Pair 1	P(untruthful)=0 - P(untruthful)=1	-.073620	.003653	.000517

Paired Samples Test

		Paired Differences		
		95% Confidence Interval of the Difference		
		Lower	Upper	t
Pair 1	P(untruthful)=0 - P(untruthful)=1	-.074658	-.072582	-142.516

Paired Samples Test

		Paired Differences	
		df	Sig. (2-tailed)
Pair 1	P(untruthful)=0 - P(untruthful)=1	49	.000

If GSP_6 can live with this untruthful client satisfaction rate, it will continue using this computing capacity (GSP_2). On the other hand, if GSP_6 prefers to keep its client satisfaction rate over 90%, it might decide to upgrade its computing capacity to the same as GSP_3. However, GSP_6 will end up with losses since revenue of GSP_3 is below the LATC curve, as presented in

Figure 7.3. As the consequence, this would not happen because GSP_6 has to have a profit. Thus, GSP_6 will not change its decision. In short, untruthful feedback does not affect the investment decision of GSP_6 in this case.

7.2.3. Case III: High Demand with Truthful Feedback

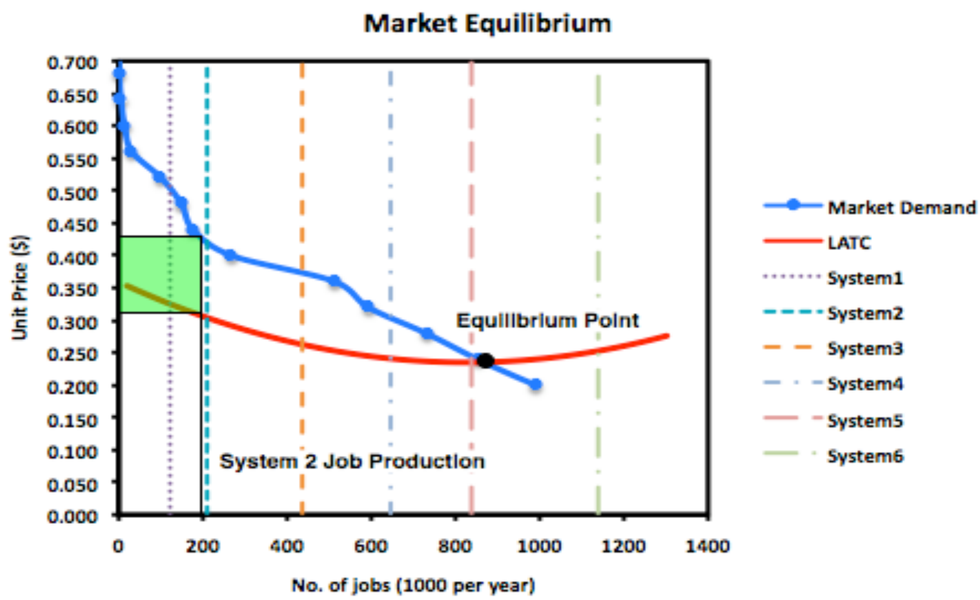


Figure 7.7 Market equilibrium in Case III, given that market demand is equal to marginal revenue.

In the high demand case, we examine whether GSP_2 should upgrade its computing capacity to generate more revenues. Without value profiles, GSP_2 produces 186,758 jobs/year and its revenue is clearly over the LATC curve. This means that GSP_2 has a super normal profit, as shown in the shaded area in Figure 7.7. Note that when a firm has a super normal profit, it attracts new entrants to the industry. On the other hand, when a firm has a normal profit, new players have a lower incentive to enter a competitive market. By increasing its capacity to produce more jobs at lower cost, a GSP would achieve economies of scale and reduce the entry incentive. Thus, GSP_2 must increase its service rate from 0.4 to 1.62 jobs/min since the equilibrium point is close to GSP_5, as shown in Figure 7.7.

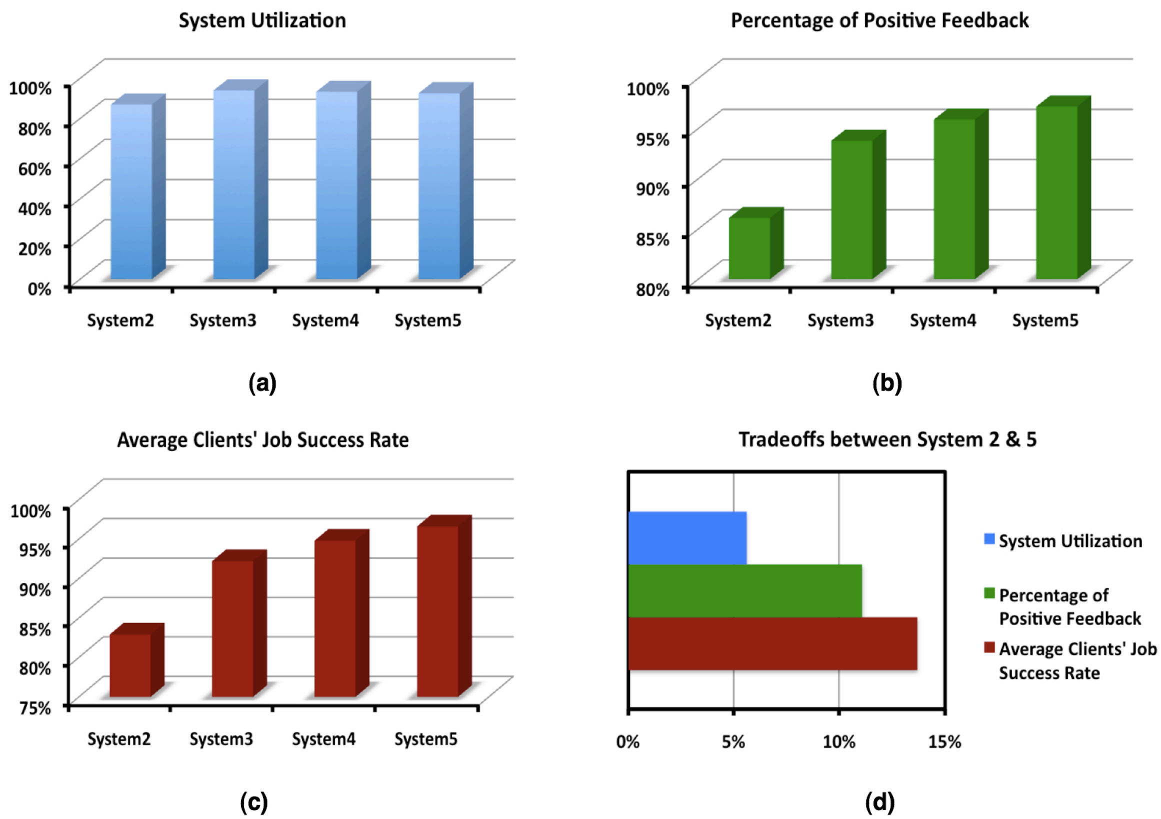


Figure 7.8 Summary of the tradeoffs when using value profiles in Case III: (a) System utilization, (b) Percentage of positive feedback, (c) Clients' job success rate, and (d) Tradeoffs when upgrading the computing capacity from system 2 to system 5.

Figure 7.8 summarizes tradeoffs involved. After upgrading to the same capacity as GSP_5, system utilization increases from 87% to 92.6%, and percentage of positive feedback goes up from 86.1% to 97.2%. Moreover, clients' job success rate significantly improves from 82.9% to 96.6%. As a consequence, there is no tradeoff in this case, as shown in Figure 7.8(d). The results visibly show that system utilization, percentage of positive feedback, and clients' job success rate increase by 5.6%, 11.1%, and 13.7% percentage points, respectively.

Table 7.12 Paired *t*-Test on the Mean of Dependent Variables when Using Value Profiles in Case III, where Pair 1, Pair 2, and Pair 3 are the *t*_Test on $\%pos\_fb_i$, ρ_i, and $\%job_{success,j}$, respectively.

Paired Samples Test

		Paired Differences		
		Mean	Std. Deviation	Std. Error Mean
Pair 1	ppf_sys2_c2 - ppf_sys5_c2	-.111520	.098390	.013914
Pair 2	rho_sys2_c2 - rho_sys5_c2	-.056480	.258119	.036503
Pair 3	success_rate_sys2_c2 - success_rate_sys5_c2	-.136180	.132015	.018670

Paired Samples Test

		Paired Differences		
		95% Confidence Interval of the Difference		
		Lower	Upper	t
Pair 1	ppf_sys2_c2 - ppf_sys5_c2	-.139482	-.083558	-8.015
Pair 2	rho_sys2_c2 - rho_sys5_c2	-.129837	.016877	-1.547
Pair 3	success_rate_sys2_c2 - success_rate_sys5_c2	-.173698	-.098662	-7.294

Paired Samples Test

		Paired Differences	
		df	Sig. (2-tailed)
Pair 1	ppf_sys2_c2 - ppf_sys5_c2	49	.000
Pair 2	rho_sys2_c2 - rho_sys5_c2	49	.128
Pair 3	success_rate_sys2_c2 - success_rate_sys5_c2	49	.000

Table 7.12 presents the difference in mean performance when using value profiles. The result shows that $\rho_2^{with\_value\_profiles}$, $\%pos\_fb_2^{with\_value\_profiles}$, and $\%job_{success,2}^{with\_value\_profiles}$ have the significant higher mean than $\rho_2^{without\_value\_profiles}$, $\%pos\_fb_2^{without\_value\_profiles}$, and $\%job_{success,2}^{without\_value\_profiles}$, respectively. These accept what are hypothesized in Q4.3-Q5.1, which are

$\rho_2^{with\_value\_profiles} > \rho_2^{without\_value\_profiles}$, $\%pos\_fb_2^{with\_value\_profiles} > \%pos\_fb_2^{without\_value\_profiles}$, and $\%job_{success,2}^{with\_value\_profiles} > \%job_{success,2}^{without\_value\_profiles}$.

In summary, the use of value profiles provides benefits to GSP_2 both in terms of revenue and client satisfaction rate. Likewise, clients receive the benefit from the use of value profiles since their job success rate goes up.

7.2.4. Case IV: High Demand with Untruthful Feedback

Like in Section 7.2.2, the purpose of this case is to determine whether untruthful feedback affects GSP_2's investment decision in case III. With truthful feedback in case III, positive feedback increases by 11.1% percentage points after GSP_2 upgrades its computing capacity to the same as GSP_5. With untruthful feedback in this case, positive feedback increases from 70.2% to 90.6%, which is 20.4% increment in percentage points as presented in Figure 7.9(b). According to the statistical testing in Table 7.13, untruthful feedback significantly inflates the accuracy of positive feedback by 9.18% percentage points.

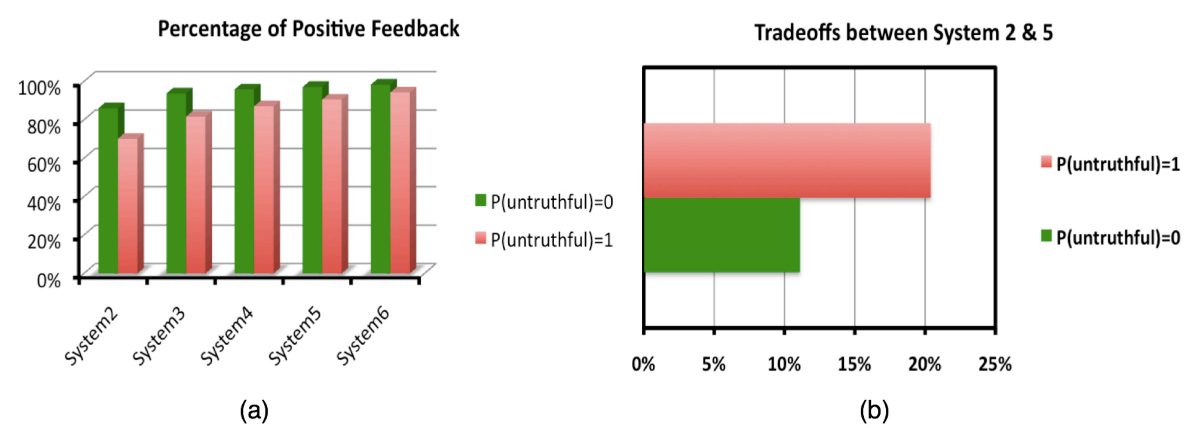


Figure 7.9 Percentage of positive feedback comparing between Case IV and III.

As this untruthful client satisfaction rate is around 90%, GSP_2 will continue using this computing capacity (GSP_5). Unless GSP_2 requires client satisfaction rate to be 95%, it might decide to upgrade its computing capacity to the same as GSP_6. To do so, GSP_2 will lose since revenue of GSP_6 is below the LATC curve, as presented in Figure 7.7. In reality, this would not happen because GSP_2 has to have a profit. Thus, GSP_2 will not change its decision. In short, untruthful feedback does not affect GSP_2's investment decision in this case.

Table 7.13 Paired *t*-Test on the Mean of Percentage of Positive Feedback Comparing between Case IV and III.

Paired Samples Test

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	P(untruthful)=0 - P(untruthful)=1	-.091820	.024517	.003467	-.098788	-.084852	-26.482	49	.000

7.3. LIMITATIONS OF RESULTS

The limitations of results from the use of credibility-based binary feedback model arise from the value profile construction approach in Chapter 5. Given those cooperative clients, the results are conditional upon this assumption. This section discusses three main issues that directly affect the experimental results.

First, we assume that clients always cooperate with GSPs. Although we study clients' incentives to cooperate in Section 6.1.2, it is still difficult to guarantee that clients will always cooperate. As discussed in Section 6.1.1, the result shows that a low *P(contribution)* affects the precision of value profiles, which can lead to an erroneous equilibrium point. In the analysis of research questions Q4-Q5 in Section 7.2, the equilibrium point has to be precise to help GSPs optimize their long run resource investment and allow us to examine the tradeoffs when using value profiles.

Second, from Table 6.16 and Table 6.29, we conclude that clients will always provide untruthful feedback and there are two cases that the model cannot filter out untruthful feedback. Moreover, as described in Section 6.4, untruthful feedback might affect GSPs' investment decision. Therefore, GSPs might use a mechanism to calibrate the received client satisfaction rate caused by the clients' misbehavior.

As described in Section 6.1.4 and Section 7.2.1, GSPs record the expected positive feedback[49]. This record can be used as the upper bound of client satisfaction rate when clients are always truthful, *P(untruthful)* = 0. Thus, the real rate would be the value between the upper

[49] GSPs expect to receive positive feedback if they can finish a job within a preferred duration, as described in Equation (6.1).

bound and the received rate. To estimate the real rate, for example, GSPs might use the average value between the upper bound and the received rate as the reference rate.

In case II, after GSP_6 downsizes its computing capacity to the same as GSP_2, the received client satisfaction rate is 85.6%. If GSP_6 prefers this rate to be over 90%, this received rate might lead to an inaccurate capital investment decision. By calibrating the received rate, the reference rate is 90.2%, as shown in Figure 7.10. Since the rate is over 90%, GSP_6 will be satisfied and not change its decision. In short, calibrating the received rate can assist GSPs making an accurate capital investment decision.

Figure 7.10 Reference client satisfaction rate, in Case II.

Like purchasing airline tickets, we have assumed that prices are fixed after GSPs and clients have an agreement. Now, we will relax this simplifying assumption with variable prices. Like international phone calls[50], GSPs will calculate actual costs based on an actual resource usage. To explore this issue, we repeat the experiments in Cases I and II. Then, we observe the change of results.

[50] For international phone call, we know the exact rate, but when start calling, we do not know how much the total costs are.

In this experiment, prices are calculated based on the total time taken from entering a system until a job is completed $t_j^{total\_computing}$, which is equivalent to the mean response time of system. As we have assumed M/M/1, $t_j^{total\_computing}$ is expressed as

$$t_j^{total\_computing} \sim \left(1 \big/ \mu_i \right) \left(1 \big/ (1-\rho_i) \right) \tag{7.6}$$

Next, we transform it into the term of ρ_i, which is expressed as

$$\rho_i = \left| \frac{\mu_i * t_j^{total\_computing} - 1}{\mu_i * t_j^{total\_computing}} \right| \tag{7.7}$$

Then, by substituting Equation (7.7) into Equation (5.1), we can express as

$$p_j^{actual} = a_i + b_i * \left| \mu_i * t_j^{total\_computing} - 1 \right| \tag{7.8}$$

Table 7.14 Change of Model Parameters for Variable Pricing

	Parameters	*Values*
CLIENT AGENTS	α_j	Uniform (0, 100)

Note: See Table 7.4-Table 7.5 for other parameters.

We change the constraint sensitivity of each client α_j, as summarized in Table 7.14. In Figure 7.11, in case I, the result shows that the difference of market demand curves for variable prices and for fixed prices is very minor. Their market equilibrium points are the same, which is close to GSP_2. Figure 7.12 also presents the comparison of tradeoffs between these two pricing scenarios. The results show that the differences are small. However, clients prefer fixed prices to variables prices, as shown in Figure 7.12 (b).

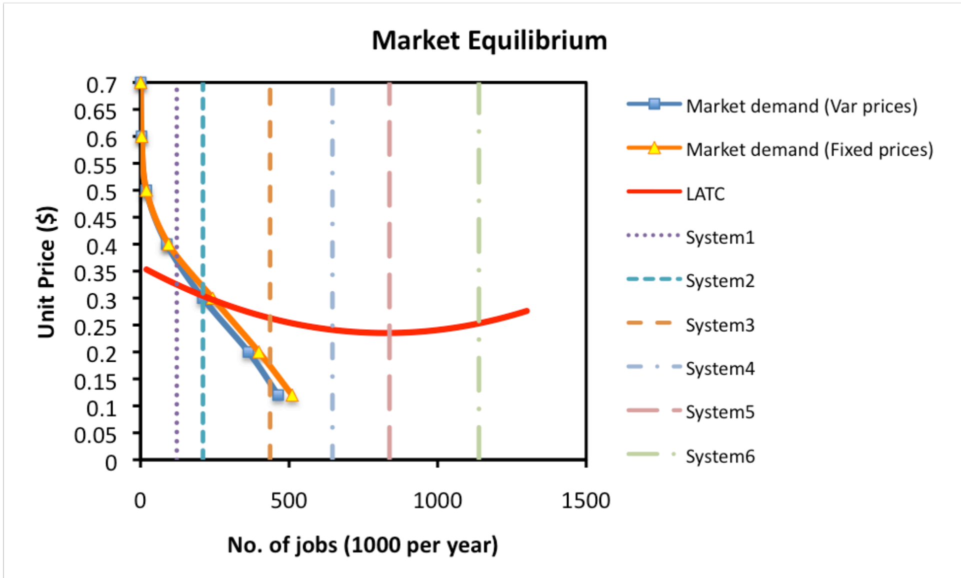


Figure 7.11 Market equilibrium in Case I, comparing between variable prices and fixed prices.

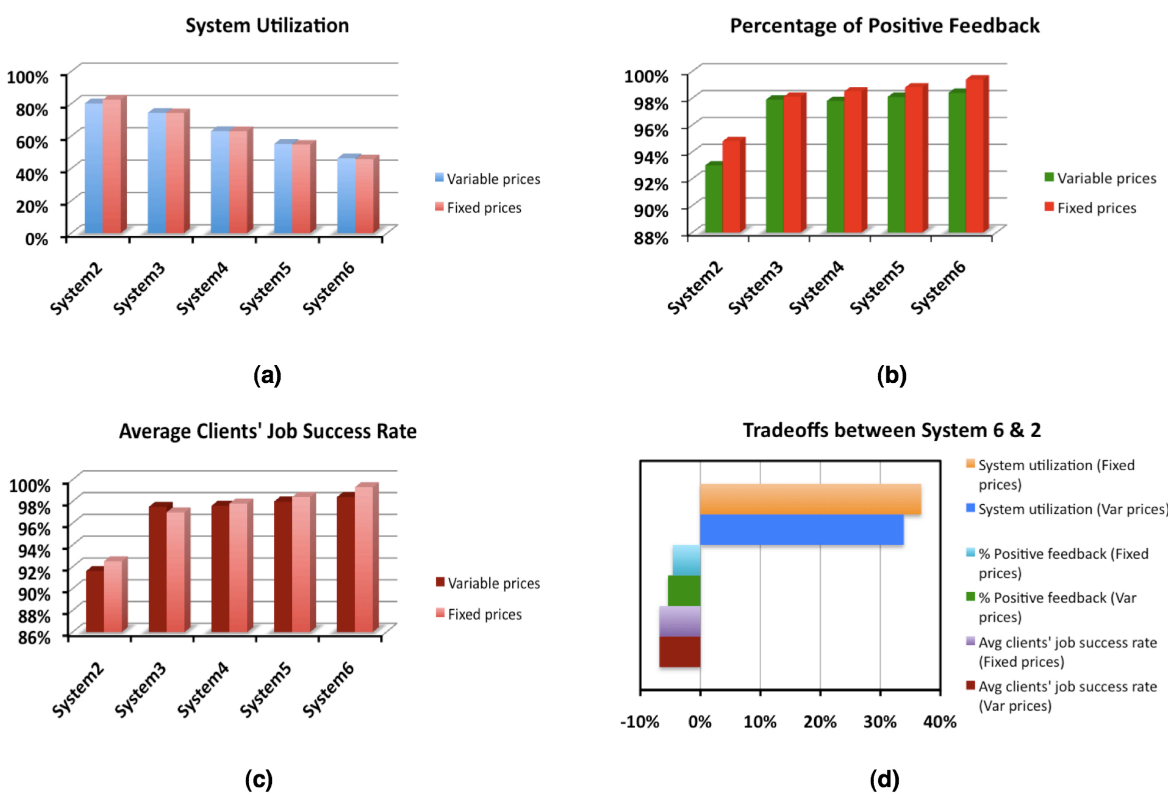
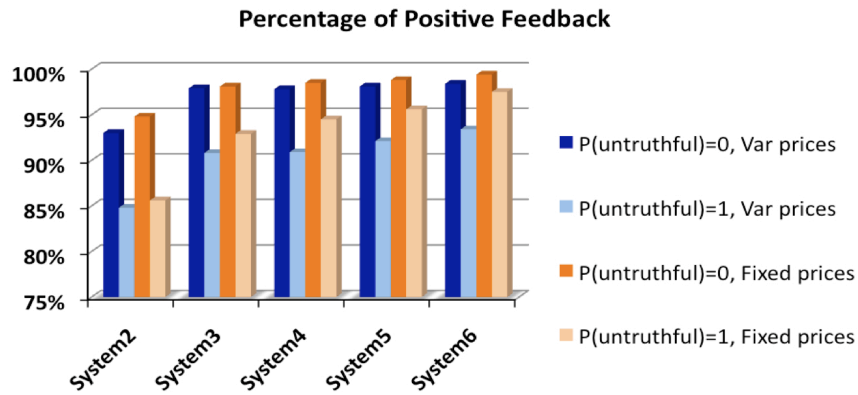
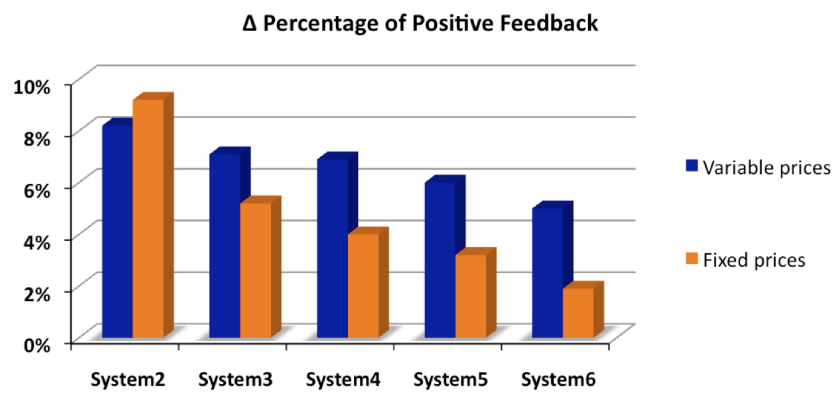


Figure 7.12 Summary of the tradeoffs when using value profiles in Case I, comparing between variable prices and fixed prices.



(a)



(b)

Figure 7.13 Changes of percentage of positive feedback in Case II, comparing between variable prices and fixed prices, (a) percentage of positive feedback and (b) the differences of percentage of positive feedback when *P(untruthful)*=1 and when *P(untruthful)*=0.

Figure 7.13, in case II, presents the comparison of percentage of positive feedback (or client satisfaction rate) between two pricing scenarios. In Figure 7.13(b), the result shows the difference of percentage of positive feedback when *P(untruthful)*=1 and when *P(untruthful)*=0.

The result also shows that untruthful feedback has more effect on variable prices. However, GSPs can diminish this effect by using the reference rate, as discussed earlier in this section[51].

7.4. MODEL IMPLEMENTATIONS

In this dissertation, we use the Demandware architecture[52] to illustrate the implementation of credibility-based binary feedback model for grid resource planning, as shown in Figure 7.14. By leveraging a grid computing architecture, Demandware can dynamically increase or decrease the share of computing capacity assigned to each client's requirement. This is to ensure that clients always have the computing capacity they need when they need it without paying for excess capacity up front [59]. Nevertheless, Demandware does not concentrate on its resource pool. To operate efficiently, Demandware has to have adequate resources to supply on-demand services as promised. Another concern is client satisfaction. Demandware does not ensure that clients are satisfied with received on-demand services in terms of QoS and cost. As a result, Demandware requires a mechanism to determine how clients value its service. With this information, Demandware can create a value profile to scale its resource pool to maximize its profit.

By employing the credibility-based binary feedback model into the Demandware architecture, it can scale its resource pool with client demand, as shown in Figure 7.14. From our recommendation, it requires grid feedback from e-commerce sites. Generally, e-commerce sites prefer to have sufficient computing capacities within their budget to satisfy their end users. Thus,

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[51] See Figure 7.10.

[52] Demandware is the leading on-demand e-commerce platform that offers the most powerful online merchandising and marketing tools with total control over the shopping experience. The Demandware architecture is based on a patented grid computing technology that delivers capacity as needed for performance, scalability, and reliability [60]. For our case, Demandware operates as a GSP while e-commerce sites act as grid clients. See http://www.demandware.com/

e-commerce sites provide feedback based on on-demand service satisfaction and end users' feedback, as presented in Figure 7.15. This feedback represents how e-commerce sites value the received on-demand service from Demandware and how end users value the received service from e-commerce sites.

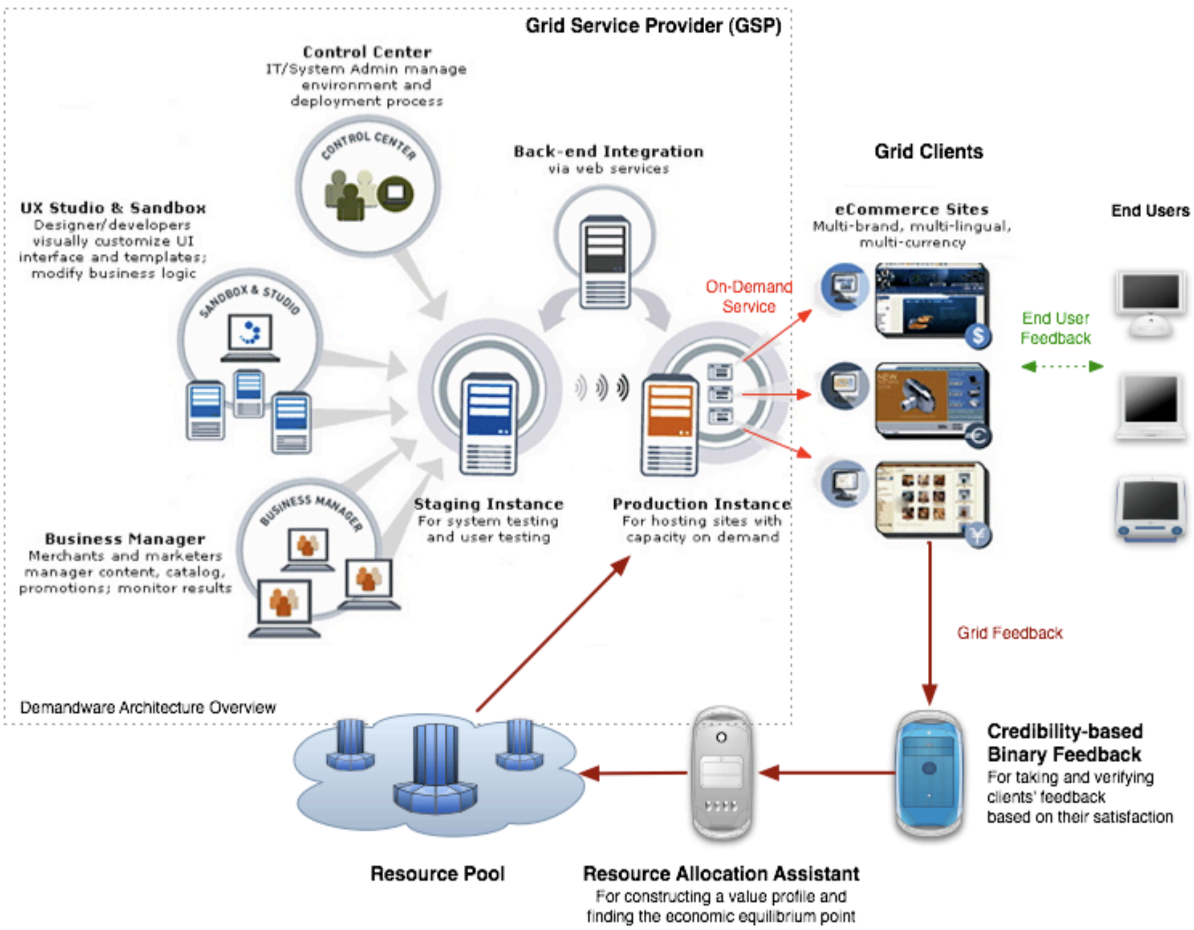

Figure 7.14 The model implementation based on the Demandware architecture [61].

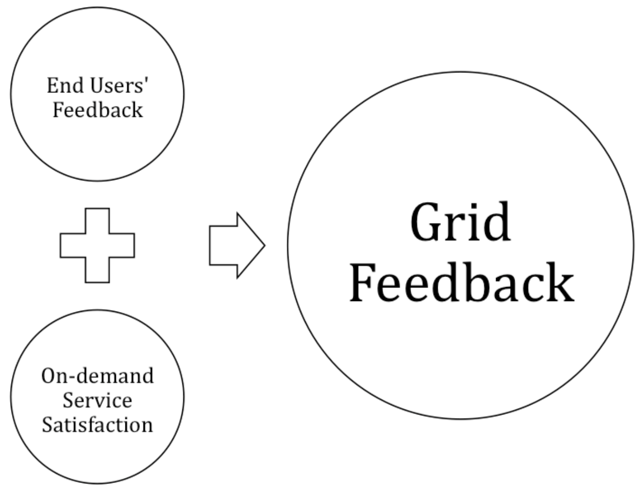

Figure 7.15 Grid feedback structure.

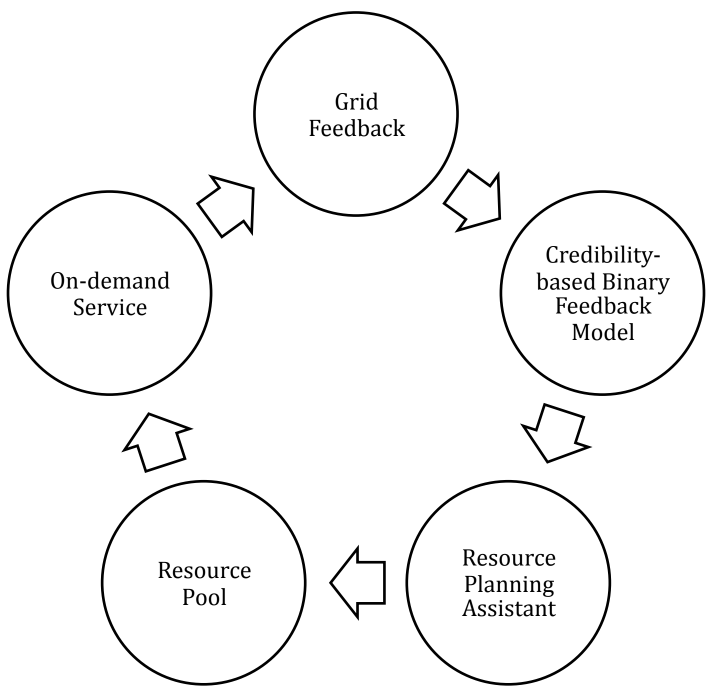

Figure 7.16 Grid resource planning process.

Given cooperative e-commerce sites and end users, they provide Demandware binary feedback based on their satisfaction. After verifying the feedback by filtering out untruthful feedback, Demandware has a value profile that can be used as a proxy for the demand from grid clients. With the value profile, the resource-planning assistant can determine an economic equilibrium point to scale its resource pool. As this process continues recursively, Demandware will have the right size of resource pool to provide on-demand services to its clients. Therefore, the value profile could help Demandware optimize their long run resource investment. Figure 7.16 summarizes the grid resource planning process.

8. CONCLUSION AND FUTURE WORK

As the goal of GSPs is to improve their economic viability by maintaining the least possible set of resources to meet client demand, they have to know how clients value their services. The main objective of this dissertation is to develop an approach to build a value profile using feedback models for a collection of grid clients so that GSPs can use the value profile to economically plan their resources. We provide a comprehensive review of grid resource management systems and grid resource allocation approaches in Chapter 2. Most studies concentrate on building market-based resource allocation, providing incentives to resource owners to contribute resources, motivating resource users to trade-off between budget and preferred duration, and investigating the efficiency of different market-based resource allocation in different aspects. However, none of them concentrates on the use of service value to grid clients. Therefore, we provide theoretical frameworks that can be used to construct a useful value profile in Chapter 4.

In this dissertation, we propose the use of binary feedback model to build a value profile. After a service, clients are allowed to rate GSPs based on their satisfaction. According to research question Q1, the following summarizes the finding of results in Chapter 5.

- The binary feedback can be used to construct a value profile that can serve as a proxy for a demand function.
- The value profile can represent client's willingness-to-pay for grid resources at different prices.

As a contribution, we examine issues necessary to be addressed when using binary feedback for a collection of clients in Chapter 6. One of the main concerns is feedback contributions. In reality, clients do not directly benefit from their contributions, while GSPs benefit more directly. With the use of individual effort model, we explain how to encourage feedback contributions. Furthermore, clients have incentives to provide untruthful feedback to consume as many resources as possible. We propose the use of credibility mechanisms to detect untruthful feedback and penalize insincere or biased clients. We also propose the use of game theory to study how the cooperation can emerge. The results in Chapter 6 show that the credibility mechanism can help the cooperation to emerge. The followings summarize the findings from game theory according to research questions Q2-Q3.

- Clients do not have incentives to be truthful because they receive more benefits when providing untruthful feedback. They want to receive a better service even though they are already satisfied with the current service.
- The credibility mechanism can be used to encourage clients to be truthful because it ensures that sincere clients always receive more benefits than insincere clients. This mechanism is definitely required for the cooperation to emerge.
- Furthermore, GSPs do not have an incentive to cheat and disregard unfavorable feedback since their feedback profiles are made public.

As the main contribution of this dissertation, we use the credibility-based binary feedback model to construct value profiles for grid resource planning. In Chapter 7, we experiment whether value profiles benefit GSPs and clients in the low demand case and the high demand case. The results show that the use of value profiles can assist GSPs in finding an economic equilibrium point to plan their resources. Such benefit would help to optimize their long run resource investment. The followings summarize the findings of statistical testing regarding to research questions Q4-Q5.

- In the low demand case, the use of value profiles assists GSPs to decrease their resource base. When using value profiles,
    - GSPs have a normal profit.
    - The number of idle resources decreases significantly.
    - Client satisfaction rate decreases slightly.
    - Clients' job success rate decreases slightly.
    - Although clients are worse off in this case, they are still better off cooperating with GSPs to avoid more delays added into systems when defecting.
- In the high demand case, the use of value profiles assists GSPs to increase their resource base. When using value profiles,
    - GSPs can achieve economies of scale.
    - The number of idle resources decreases.
    - Client satisfaction rate increases significantly.
    - Clients' job success rate increases significantly.

As clients always provide untruthful feedback and there are some cases that the model cannot filter untruthful feedback, we assert that a feasible way to calibrate client satisfaction rate is to use GSPs' expected positive feedback as the upper bound rate. This helps GSPs to estimate the real rate, which is the value between the upper bound and the received rate. The estimated real rate can be used as a reference client satisfaction rate for GSPs when making a capital investment decision.

We also introduce the model implementation over the Demandware architecture in Chapter 7. As the implementation costs are low, we believe that the use of credibility-based binary feedback can help Demandware optimize their long run resource investment.

The following summarizes the contributions of this dissertation.

- I build the service satisfaction function in terms of the change in computing time and the change in computing cost. This function allows heterogeneous grid clients to express whether they are satisfied with the received service.
- As the main contribution, I use binary feedback as the framework to build a value profile, which can be used as a proxy for a demand function. This proxy can represent clients' willingness-to-pay for grid resources.
- In order to study cooperation and trust between GSPs and clients, I build the exponential-decay value function that represents the QoS that the client received from the GSP. In this function, the client's perceived value is proportional to the difference between preferred duration and total computing time. The longer the total computing time, the less the client's perceived value will be.
- Another key contribution is that I provide credibility-based binary feedback model to filter out untruthful feedback. The summation of resulting value profiles can be used as a proxy for market demand. This proxy can assist GSPs to find an economic equilibrium point to scale their resource pool. Therefore, this model helps GSPs optimally plan their resources and optimize their profits.

The followings discuss the possibility of extending the credibility-based binary feedback model for grid resource planning.

- The experiments on the model are currently simplified by ignoring the role of resource brokers. In reality, clients might submit a job with their constraints through brokers and let them handle the rest. Thus, GSPs might not know true clients' constraints unless brokers share this information. However, brokers might not share it with GSPs if they do not have economic incentives to do so. Future work can study how to create incentives for brokers to cooperate.
- We have assumed that jobs have the same size. In reality, this may not apply. Since clients may submit variety of different sizes of jobs to the grid, estimated computing time of each job must be taken into account when calculating its estimated price. To do so, an appropriate mechanism is required to estimate computing time of each request.
- In the current model, there is no discount rate for clients when GSPs miss a preferred duration. Future work may include this rate when calculating client satisfaction. Although clients receive a result back after a preferred duration, they might still be satisfied with that service if they are happy with that discount rate. However, this does not mean that they are really satisfied with the service and willing to pay for it at the future time. Thus, future work can study the effect of discount rates on a true client satisfaction.
- Instead of given demand scenarios, future work can study whether the model can be used to forecast market demand. To do so, GSPs might require further information from clients. This raises the question on what further information GSPs should obtain from clients.
- Instead of commodity markets, future model may include other market models, such as auction and bargaining, and study their effectiveness.

- Future work can be extended to study the duration time for storing feedback data. As the model uses feedback data to construct a value profile as a proxy for a demand function, the data should be stored in a timely fashion to obtain the precise demand. GSPs might have to eliminate an out-of-date data. The challenge is finding the maximum time interval for storing the data.
- To calibrate client satisfaction rate, we have used GSPs' expected positive feedback as the upper bound rate. We have estimated the real rate by calculating the average value between the upper bound and the received rate. Instead of using the average value, future work can be extended to study other estimating methods. Furthermore, future work may improve the detection of untruthful feedback.
- We have assumed that when any GSP decides to change its resource base affected by market demand, other GSPs will not change their resource base. Future work can examine strategic interactions among GSPs. Given that, market equilibrium point would be affected by the action of any GSPs in the market. Therefore, the first resulting equilibrium point will no longer be the optimal point for planning their resource base and will not provide the maximum profits.

APPENDIX A

Server Cost of Ownership from TPC-C Benchmark

Table A.1 GSP_1: IBM System p5 570 Oracle 10g Release 2 Enterprise Edition

System # 1	Description		3-yr Cost
Server Hardware	IBM System p5 570		40,200
	2-Way 2.2GHz POWER5+ Processor Card, 0-way active, 8 DDR2		27,400
	One way Processor Activation for Processor FC 8338		54,800
	Op Panel		199
	Processor Cable		2,647
	SP Flex Cable		1,324
	16GB (4x4GB) DIMMS, 276 PIN, 533MHz, DDR2 SDRAM		242,480
	73.4GB 15K RPM Ultra320 SCSI Disk Drive		1,318
	4Gb Dual Port Fibre Channel		16,540
	IDE Slimline DVD-ROM Drive		274
	Processor Power Regulator		4,050
	CEC Backplane		3,176
	I/O Backplane		10,852
	Midplane		1,324
	DASD Backplane		3,176
	Media Backplane		185
	Power Midplane		530
	System Port Riser Card		264
	AC Power Supply, 240V, 1400W		4,236
	FSP Service Processor Card		860
	Power Cord, Drawer to IBM PDU 250V/10A		76
	IBM Rack-mount Drawer Rail Kit		444
	System Drawer Enclosure w/Bezel		926
	Desktop Hardware Management Console		1,830
	IBM T541H/L150P 15"TFT Display		508
	IBM Full Width USB Keyboard		104
	IBM 3-Button Optical Mouse - Black - USB		78
		Subtotal	419,801
Server Storage	IBM System Storage EXP3000		67,179
	IBM 3M SAS cable		5,670
	IBM DS3000 Environmental Services Module (ESM)		20,979
	IBM System Storage DS3400 Dual Controller Express		69,992
	IBM Hot-Swap 3.5 inch 73.4GB 15K SAS HDD		93,936
	IBM S2 42U Standard Rack		2,978
	DS3400 Software Feature Pack		6,965
	DS3000 Partition Expansion License		13,965
	D-LINK DGS-1024D 24-Port 10/100/1000 Switch (2 spares)		609
	ServicePac 24x7x4 Support (DS3400)		10,400
	ServicePac 24x7x4 Support (EXP3000)		15,960
	ServicePac 24x7x4 Support (Rack)		600
		Subtotal	309,233
Server Software	Oracle Database 10g Release 2 Enterprise Edition, Per Processor		60,000
	Oracle Database Server Support Package		12,000
	Oracle Mandatory E-Business Discount		(6,600)
	Red Hat Enterprise Linux Advanced Platform, Premium		7,497
		Subtotal	72,897
		Total IBM Discounts	(230,543)
Available 04/04/08		**Three-Year Cost of Ownership USD:**	**$571,388**

Table A.2 GSP_2: IBM System p 570 Model 9117-MMA

System # 2	Description		3-yr Cost
Server Hardware	Server 1:9117 Model MMA		17,341
	GX Dual Port- 12X Channel Attach		1,499
	Op Panel (MMA)		199
	73.4GB SAS DASD, 15K RPM		1,318
	One Processor Activation for Processor Feature #7380		107840
	P6 Processor Power Regulator		4,500
	System CEC Enclosure with Bezel		500
	AC Power Supply, 200-240v, 1500 Watt		3,004
	Media Enclosure and Backplane		185
	I/O Riser, 2x Serial, 2x p5IO2C E'net (Evans)		399
	Service Processor Interface		1,000
	Processor Enclosure and Backplane		2,000
	I/O Backplane		4,500
	System Midplane		1,000
	SAS DASD Backplane, 6-pk		1,051
	Activation of 1GB DDR2- P6 Memory		290,880
	0/32GB DDR2 Memory (4X8GB) DIMMS- 400 MHz- POWER6 Memory		161,316
	System Ship Group		20
	IDE Slimline DVD-ROM Drive		275
	2-Port 10/100/1000 Base-TX Ethernet PCI		699
	Line Cord, DRWR TO IBM PDU, 14', 200-240V/10A,		38
	Rack Mount kit for IBM 19" rack		222
	4.7GHz POWER6 -2 Core Processor Card, 0-core active		31,592
	Power Distribution Backplane		265
	IO Drawer 7314-G30		7,931
	1.5M 12X ENHANCED IB CABLE		800
	4 Gb Dual-Port Fibre Channel PCI-X 2.0 DDR		12,495
	POWER CONTROL CABLE, 3M, (SPCN)		80
	AC Power Supply 300 Watt		600
	Dual Port 12X Channel Adapter		575
	Line cord		28
	Planer and Tray Assembly		1,300
	Power Controll SPCN		250
	I/O Drawer Mounting Enclosure		525
	Rack Model T00		3,688
	Front Trim Kit For 1.8 Meter Rack (Black)		158
	Side Panel (Black)		300
	PDU to 14', 200-240V/24A, UTG0247, PT#12		240
	HMC 1:7310-C05 Desktop Hardw.Mgmt.Console		3,174
	IBM ThinkVision C170 17-inch Color Monitor		250
	Power Cord (6-foot), To Wall Plug Type #4		36
	Ethernet Cable, 6M, HMC to System Unit		15
	Keyboard - English, #103P		104
	Mouse - Attachment Cable		78
		Subtotal	664,270
Server Storage	DS4800 Disk System Model 82		269,975
	DS4800 8-Storage Partitions		50,000
	(22R4255) DS4800 AIX Host Kit		35,000
	DS4000 EXP810 Enclosure		312,000
	36GB/15K Drive 4Gb FC disks		695,760
	Short Wave SFP		51,896
	Fiber Cable 25m		1,890
	Fiber Cable 1m		8,216
	Warranty Service Upgrade 1812-81A 24x7x4		49,920
	Warranty Service Upgrade 1815-82A 24x7x4		16,000
		Subtotal	1,490,657

Server Software	AIX 5.3 (media only)	50
	AIX Software per Processor	4,900
	Software Maintenance for AIX	
	F5 SWMA for AIX per Processor	7,832
	F5 Services 7x24 Support per Processor	1,984
	Partition Load Manager SW Maint	
	F5 SWMA for AIX per Processor	220
	F5 Services 7x24 Support per Processor	56
	VIO Software Maintanance	
	Per Processor F5 VIO Maintenance	980
	Per Processor F5 VIO Maint 24x7 Support	256
	Initial Software Support	
	Per Processor Software Support	675
	Per Processor 24x7 Software Support	236
	C for AIX user Lic+SW maint	515
	C for AIX user annual SW maint renewal	206
	Oracle Database 10g Enterprise Edition, Per Processor, Unlimited Users	60,000
	Oracle Database Server Support Package	6,000
	Subtotal	83,910
	Total IBM Discounts	(903,098)
Available 11/26/07	**Three-Year Cost of Ownership USD:**	**$1,335,739**

Table A.3 GSP_3: IBM System x3950 M2 c/s Microsoft SQL Server 2005

System # 3	Description		3-yr Cost
Server Hardware	IBM System x3950 M2 (2 x Intel Xeon Processor X7350 with 2.93GHz/2x4MB L2 Cache, 4 Memory Cards, 8 x 1GB DIMM, onboard SAS enablement key, cables)		38,938
	Intel Xeon Processor X7350 (2.93GHz/1066MHz FSB/2x4MB L2)		19,196
	16GB (2x8GB) 667MHz PC2-5300 ECC DDR2 SDRAM DIMM		960,000
	ServeRAID-MR10M SAS/SATA Controller		1,049
	73.4GB 15K Hot Swap SAS		309
	IBM T115 15-inch TFT Display		209
	IBM Preferred Pro USB Keyboard		29
	IBM 3-Button Optical Mouse - Black - USB		19
	NetXtreme II 1000 Express Ethernet Adapter		558
	PRO/1000 PT Dual-Port Server Adapter		269
	ServicePac 24x7x4 Support (x3950 M2)		6,780
	ServicePac 24x7x4 Support (Display)		90
		Subtotal	1,027,446
Server Storage	IBM 4Gb FC Dual-Port PCI-E HBA for IBM System x		5,316
	IBM System Storage DS4800 Midrange Disk Subsystem		377,965
	4 Gbps SW SFP Transceiver 4 Pack		18,150
	IBM 1m LC-LC Fibre Channel Cable		13,272
	IBM 5m LC-LC Fibre Channel Cable		2,709
	IBM System Storage DS4000 EXP810 Storage Exp. Unit		504,000
	36.4GB 15K 4Gbps FC E-DDM Hot-Swap HDD		1,198,848
	IBM TotalStorage SAN16B-2		8,240
	B16 4-Port Activation		3,140
	IBM System Storage EXP3000		6,398
	500GB 3.5" Dual Port Hot-Swap SATA II		12,400
	IBM EXP3000 1m Cable		238
	IBM UPS 750TLV		299
	IBM S2 42U Standard Rack		11,912
	ServicePac 24x7x4 Support (EXP810)		80,640
	ServicePac 24x7x4 Support (DS4800)		22,400
	ServicePac 24x7x4 Support (SAN16B-2)		2,240
	ServicePac 24x7x4 Support (EXP3000)		1,520
	ServicePac 24x7x4 Support (Rack)		2,400
		Subtotal	2,272,087
Server Software	Microsoft SQL Server 2005 Enterprise x64 Edition		199,992
	Microsoft Windows Server 2003 R2 Enterprise x64 Edition		3,999
	Microsoft Problem Resolution Services		245
		Subtotal	204,236
		Total IBM Discounts	(686,583)
Available 04/01/08		**Three-Year Cost of Ownership USD:**	**$2,817,186**

Table A.4 GSP_4: NEC Express5800/1320Xf C/S with Express5800/120Ri-2

System # 4	Description	3-yr Cost
Server Hardware	Express5800/1320Xf system	1,971,736
	Cabinet w/8cells&1IO	
	4 Itanium2 CPU(1.6G/24M) for 1320Xf	
	1320Xf Memory 16GB (4x4GB DIMM) memory kit	
	Memory Slot Expansion Module Option	
	IO Expansion Cabinet	
	IO Enclosure	
	1320Xf IO partition (Core)	
	1320Xf IO partition (Non-core)	
	73GB Ultra SCSI HDD 10k RPM	
	SCSI card	
	1port 10/100/1000 base-T LAN card	
	Basic Warranty Extension for Year 2 and 3	
	Year 1,2 &3 4 hour HW maintenance	
	NEC Express5800/120Ri-2 (for System Maintenance)	6,695
	120Ri-2,XD2/3.0G/2G N8100-1248F	
	CPU Kit (XD2/3.0G(4))	
	Additional 2G Memory Board	
	1000Base-T NIC Dual Channel	
	Additional 36.3 GB HDD	
	Warranty Extension Year2&3	
	3Year 4h 24x7 support	
	NEC AccuSync500 (15" monitor)	480
	FC HBA QLA2342 (+10% spares)	47,760
	FC HBA QLA2462 (+2 spares)	5,052
	Subtotal	2,031,723
Server Storage	NEC Storage D3-10 Base Model	1,344,000
	SAS/SATA Enclosure	453,600
	SAS disk drive (15k rpm/147GB) (+10% spares)	2,938,850
	Software Base Product D3-10 Lite	571,200
	4hr onsite maintenance service	473,645
	Extended 1 year software warranty - per title	342,720
	NEC Storage S2500 Base Model	31,000
	S2500 FC Disk Expansion Box	18,600
	Fibre channel disk drive (15k rpm/73GB) (+10% spares)	80,520
	4hr onsite maintenance service	13,012
	42U Rackframe	16,191
	FC Cable 10M LC-LC (+10% spares)	4,750
	Subtotal	6,288,088
Server Software	Red Hat Enterprise Linux Advanced Platform, Premium (Unlimited Sockets)	7,497
	Oracle Database 10g Enterprise Edition Per Processor, Unlimited Users	320,000
	Partitioning, Per Processor, Unlimited Users	80,000
	Database Server Support Package	6,000
	Subtotal	413,497
	Total NEC Discounts	(3,858,455)
Available 04/30/08	**Three-Year Cost of Ownership USD:**	**$4,874,853**

Table A.5 GSP_5: Bull Escala PL1660R

System # 5	Description		3-yr Cost
Server Hardware	ESCALA NODE PL1660R (BASE DRAWER)		27,357
	INDICATOR SYSTEM PL1660R PACKAGE		
	4.7GHZ P6, 2-CORE PROCESSOR CARD, 0-CORE ACTIVE		134,610
	PROCESSOR POWER REGULATOR		18,000
	ACTIVATION OF 256GB DDR2 POWER6 MEMORY		1,163,520
	ONE PROC.ACTIVATION FOR 2-CORE&4.7 (P6)		448,256
	EXPANSION CPU DRAWER FOR PL1660R		40,626
	EXPANSION PCI-X I/O DRAWER		41,322
	73 GB SAS DISK DRIVE (1"/15KRPM)		1,318
	2X- 1GB VIRTUAL ETHERNET (RJ45) AND 2 SYSTEM		1,596
	10/100/1000 BASE-TX ETHERNET PCI-X ADAPTER		2,120
	2-PORT 10/100/1000 ETHERNET PCI-X ADAPTER		755
	4GB/S FIBRE CHANNEL PCI-X ADAPTER 2-PORT		52,500
	GX DUAL PORT - 12X HCA		1,499
	IDE SLIMLINE DVD-ROM DRIVE		275
	RACK 36U (BLACK) WITH ONE PDU - 12 OUTLETS		5,778
	POWER SUPPLY TYPE EU		
	17" FLAT PANEL MONITOR		890
	FULL WIDTH QUIET TOUCH KEYBOARD - USB, FR		100
	ADDITIONAL POWER DISTRIBUTION UNIT - SINGLE PHA		1,000
	0/256GB (32X8GB) DDR2, 400MHZ, 0GB ACTIVE		291,378
	MEDIA ENCLOSURE AND BACK PLANE		185
	KIT INTERCONNECT FOUR-DRAWER CABLES		30,000
	KIT CABLES/FIRST EXPANSION DRAWER		515
	I/O DRAWER MOUNTING ENCLOSURE (2 POSITIONS)		1,050
	OPERATOR PANEL		199
	DESKSIDE HMC W/O MONITOR/KEYBOARD		3,282
	POWER CORD PDU/WALL (4.3M), 48A IEC309, 63A PLUG		480
	POWER CORD (14-FOOT) - DRAWER TO PDU		240
	NUMBER OF AIX PARTITIONS		
	ADVANCED POWER VIRTUALIZATION (PER CPU)		20,960
	cable IB 3M		1,680
		Subtotal	2,291,491
Server Storage	DS4800 Disk System Model 82		1,133,895
	DS4800 8-Storage Partitions		210,000
	(22R4255) DS4800 AIX Host Kit		147,000
	DS4000 EXP810 Enclosure		1,488,000
	72GB/15K Drive 4Gb FC disks		282,072
	36GB/15K Drive 4Gb FC disks		2,954,304
	Short Wave SFP		184,630
	Fiber Cable 25m		7,938
	Fiber Cable 1m		39,184
	Warranty Service Upgrade 1812-81A 24x7x4		238,080
	Warranty Service Upgrade 1815-82A 24x7x4		67,200
		Subtotal	6,752,303
Server Software	AIX 5.3 (media only)		50
	AIX Software per Processor		19,600
	Software Maintenance for AIX		36,384
	Partition Load Manager SW Maint		960
	VIO Software Maintanance		6,480
	Initial Installation PL1660R		500
	C for AIX user Lic+SW maint		1,080
	C for AIX user annual SW maint renewal		420
	DB2 Enterprise Proc 9 Lic Maintenance		519,533
	DB2 9 Enterprise Edition Proc Maint Renew		49,498
		Subtotal	634,505

	Total Discounts	(4,292,128)
Available 12/16/07	**Three-Year Cost of Ownership USD:**	**$5,386,171**

Table A.6 GSP$_6$: FUJITSU PRIMEQUEST 580 c/s w/96 Front-Ends

System # 6	Description		3-yr Cost
Server Hardware	PRIMEQUEST 580 Base Unit		247,368
	System Board		144,000
	CPU Module(Dual core Itanium2 9050/1.6GHz/24MB L3/533MHz		1463,808
	32GB Memory Module (4x8GB DDR2-400)		4,956,160
	I/O Unit		105,000
	BMC Module		1,720
	Disk Drive Unit (3.5inch, 73GB, 10,000rpm, Ultra320)		680
	Gigabit Switch Board (w/ 8 external 1000Base-T ports)		23,700
	Additional Power Supply		7,600
	External I/O Cabinet		20,850
	PCI-Box		20,700
	PCI Unit		15,510
	PCI Unit Cable (5m)		2,670
	FibreChannel Card (4Gbps, PCI-X, dual port)		153,720
	FibreChannel Cable (15m, LC-LC)		23,760
	Flat Panel Display		4,830
	USB Keyboard		50
	USB Mouse		26
		Subtotal	7,192,152
Server Storage	ETERNUS8000 Model900 Base Unit w/ 2 Controllers, 4 Drive Enclosures		2,833,452
	Additional Expansion Rack		216,000
	Additional Controllers (2 sets)		360,000
	Cache Memory (2GBx4)		232,137
	FibreChannel Host Interfaces (4Gbps, dual port, 2 sets)		460,800
	Drive Enclosures for Base Unit (4 sets)		354,600
	Drive Enclosures for Expansion Rack (4 sets)		1,674,000
	Disk Drive Unit (73GB, 15,000rpm)		2,578,176
		Subtotal	8,709,165
Server Software	Red Hat Enterprise Linux 4 AS (for Intel Itanium)		12,627
	Oracle Database 10g Enterprise Edition, Unlimited Users, Per Processor		640,000
	Partioning, Unlimited Users, Per Processor		160,000
	Oracle Database Server Support Package		6,000
		Subtotal	818,627
		Total Discounts	(7,306,930)
Available 04/30/08		**Three-Year Cost of Ownership USD:**	**$9,413,014**

GLOSSARY

Agents

Agents are autonomous entities capable of making decisions based on their behavior, perspective, and encapsulated information. They can communicate and exchange information with each other to accomplish their own goals.

Biased Clients

Biased clients are clients who have an incentive to provide an unfair rating.

Client's Budget

Budget is an amount of money available for each client to pay for a service in order to finish his/her total jobs.

Client's QoS threshold (λ_j)

Quality of service (QoS) threshold of each client represents the minimum level of service satisfaction that he/she can accept.

Computing Time

Computing time is the duration from submitting a job until receiving its result back.

Computing Cost

Computing cost is an amount of money that a client has to pay for a service. The computing cost can be either fixed or variable. The fixed computing cost is a fixed amount of money that a client agrees to pay after a service. The variable computing cost is calculated based on the actual resource consumption.

Cooperation

Cooperation is a term used to describe a situation when clients always provide truthful feedback after a service.

Credibility Mechanism

Credibility mechanism is a mechanism that allows GSPs to detect untruthful feedback and penalize insincere or biased clients.

Demand Theory

The law of demand is usually presented as an inverse relation of price and quantity (such as the number of jobs). The higher the service price, the less the client will demand.

Dominant Strategy

A dominant strategy occurs when one strategy provide a better payoff than another strategy for one player, no matter what the other players are doing.

Economies of scale

Economies of scale refers to the decreased cost per unit as production is increased.

Grid

Grid refers to an infrastructure that enables the use of computing capacities owned and managed by multiple organizations.

Grid Resources

Resources refer to CPU cycles, memory space, disk space, and network bandwidth.

Grid Resource Management System (Grid RMS)

Grid RMS is a system developed to manage or allocate grid resources owned by multiple organizations.

Grid Service Provider (GSP)

GSP is an agent who controls grid resources and sells computing capacity to clients as requested.

Heterogeneous Grid Clients

Heterogeneous grid clients are clients who have different preferences in term of budgets and preferred durations.

Insincere Client

Insincere clients are clients who have an incentive to cheat.

Inverse Demand Curve

An inverse demand curve represents the amount of goods (quantity) that buyers are willing to pay at various prices.

Long-Run Average Total Cost (LATC)

LATC is the unit cost of producing a service in the long run when all costs are variable.

Market Demand

At any price, market demand is the sum of the quantities demanded by each individual's demand.

Normal Profit

Normal profit is a zero economic profit (where revenue equals cost) since economic profit does not occur in a perfectly competitive market in long-run equilibrium because of the free entry and exit of GSPs.

P(contribution)

P(contribution) is the probability that clients will provide feedback after a service.

P(untruthful)

P(untruthful) is the probability that clients' feedback is untruthful.

Preferred Duration

Preferred duration is the latest time by which client's job should be completed.

Rational Player

A rational player is a player who makes a choice based on his/her maximum payoff without any concern for the other player's payoff.

Satisfaction

Satisfaction means services were within clients' budget and met clients' preferred duration.

Stakeholder

Stakeholder is an individual in a system having an interest in one's payoff.

Untruthful Feedback

Untruthful feedback is a term used to describe a feedback received from insincere or biased clients.

Value Profile

A value profile is a proxy for a demand function that represents client's willingness-to-pay for grid resources.

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