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Chapter 13

Market Based Resource Allocation for Differentiated Quality Service Levels

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13.1 Introduction

The emergence of the Grid makes it possible for researchers and scientists to access and share computation and storage resources across the organization boundaries. In a grid environment, individual users have their own service requirements, that is, they may demand different levels of quality of service (QoS) in terms of availability, reliability, capacity, performance, security, etc. Each QoS property imposes various constraints and performance trade-offs. Because of the complexity of managing client-specific QoS requirements and the dynamism inherent in supply and demand for resources, even highly experienced system administrators find it difficult to manage the resource allocation process. In the real world, markets are used to allocate resources when there are competing interests, with a common currency used as the means to place a well-understood and comparable value on items. Given the nature of distributed resource management, it is natural to combine economic methods and resource management in grid computing to provide differentiated quality service levels. A market based model is appealing in grids because it matches the reality of the situation where clients are in competition for scarce resources. It holds the hope that it will provide a simple, robust, mechanism for determining resource allocations. However, before we can apply a market model to a grid, there exist two challenges that we must address.

First, the model should be able to scale to a large number of machines and clients. Traditional economic models have been studied for distributed resource brokering and these approaches usually focus on optimizing some global system-wide metric such as performance. In order to compute the market clear price, these approaches need to poll or estimate the global demand and supply from providers and consumers, which inevitably incurs high communication and computation overheads, and is inherently non-scalable. Second, it is crucial that the model has the capability of supporting many QoS points in the QoS space simultaneously. The model must not be one size fits all, because a particular client will likely value one QoS property more than others. For example, a client who analyses data or runs data mining tasks may wish to have high performance data access to cache space of temporary data, but may not care whether data are secured or permanently lost once the application completes. In another example, a client who archives critical data may desire a highly reliable storage at the cost of a degraded performance. The presence of this variety in QoS should allow the model to evaluate the trade-offs and provide differentiated grid services at a level that satisfies the QoS properties for each client with a specific budget.

In this chapter, we will present two models, an auction market model where the providers offer resources and bid for consumers, and a posted-price market model where providers periodically adjust the price of resources that are available for purchase. Note that we use providers and sellers, consumers and buyers, interchangeably in this chapter. In a grid system the resource providers typically possess dynamic characteristics such as work load and connectivity. For example, two machines may be able to supply the same amount of storage resources, however, the machine with higher availability and reliability will likely charge more for the better service. Our models distinguish producers by the resource quality they provide. Furthermore, our models deal with various QoS aspects of storage services. This leads to a more complex cost function that can determine the cost of a storage service from its QoS guarantees. To demonstrate the effectiveness of the models, we present a storage grid called Storage@desk (SD) and demonstrate how they work in SD. Storage@desk is a new virtual storage grid that can aggregate free storage resource on distributed machines and turn it into virtual storage pool transparently accessible by a large number of clients. We evaluate our models using a real world trace and present the results.

The rest of the chapter is organized as follows. First, we discuss the background in Section 13.2. Next, we present Storage@desk and its market models in Section 13.3 and 13.4. The evaluation results are presented in Section 13.5. Finally, we give some future research directions in Section 13.6 and conclude in Section 13.7.

13.2 Background

A trade involves the exchange of goods, services, or both. The invention of money allows the indirect exchange in the markets where prices can be determined in many forms. Bargaining market was a dominating business practice for thousands of years, where the buyer and seller continue to improvise their offers during a trading time window and accept or reject each other's offer at the end of the negotiation. Both parties favor an agreement that maximizes their own utility. In this case, the buyer and seller are in direct communication and their offers are not extended to all possibly interested parties. Although bargaining is not disappearing, this ancient practice has given ways to auction market and posted-price market, especially with the advance of the internet and electronic commerce that shares the similar environment with our storage market. A few limitations can be blamed. First, bargaining involves a time cost as the buyer and seller negotiates for a final price to be agreed upon. In cases where time is critical, it would be difficult for both sides to reach a consensus within a short time window. They may have to make a compromised decision due to the time pressure. Second, as each side deals with only one other party, the information gathered by each side could be very limited that may also lead to a compromised decision. As a result, in both situations even if a consensus can be made, either side may possibly dissatisfy with the result because the utility is not maximized due to lack of time or information. Last, bargaining often needs human involvements in each stage of the negotiation process and autonomic bargaining remains an open research question. Therefore, with a few exceptions such as priceline.com (where a customer can name a price), internet marketplace has adopted auction and posted-price as dominant forms of practice.

Auction market [1] [2] [3] [4] has many variations depending on participants, bids, and time limits. For example, buyers bid for goods or services in a demand auction, sellers offer them in a supply auction, or both can participate in a double auction. For another example, participants may reveal their bids in an open bid auction and repeatedly bid in a continuous auction, whereas bids are kept secret in a closed auction. In this chapter, we choose to focus our attention on sealed-bid first-place auction for the following reasons. First, sealed-bid auction by nature prevents the buyers from knowing each other's bids, thus each buyer can evaluate the utility individually and make a quick decision on bids. It simplifies the bidding process and facilities the exchange of money and services. This is a highly desirable property in electronic commerce where minimum human intervene is needed. Second, because the winner is required to pay the highest price, it encourages the participants to reveal their true valuations. However, auction market has some limitations too. From the perspective of a buyer, she can only deal with one seller at one time and is uncertain about the result. The buyer having to commit to a resource quantity and price without knowing whether they will receive the resource makes it difficult to reason about how to accomplish a resource allocation. Also, the opportunity cost is quite high when a buyer has to go through several auctions before wining one. From the perspective of a seller, she may be forced to sell at an undesirable price when there is lack of competitions, or unable to sell the desired quantity when there is lack of bids.

Posted-price market in electronic commerce is a nature extension from our daily experience, that is, we pay goods or services for the specified price in supermarkets, gas stations, restaurants, etc. The most significant advantage is that posted prices facilitate quick transactions. This makes possible by the sellers publicly announcing their prices. Knowing the price, the buyer can reach a decision locally and other buyers' decision has no adverse effect if the seller has unlimited quantity of goods to offer. Furthermore, a buyer can potentially collect the prices from many sellers and make "smart" decisions. In the meantime, a seller can be certain about the profit when a transaction occurs. Compared to auction market where the buyers have to decide whether to bid, to whom, and at which price, posted-price market requires the sellers to decide at which price to sell, for how many, and for how long. The burden is now on the sellers' shoulders.

In addition to bid-based models, previous research on applying market methods on distributed resource management has focused on commodity market models, where a resource is viewed as interchangeable commodity in a commodity market, in which the consumers buy the resource from the providers at a publicly agreed market price. G-commerce [5] is an example of this commodity market model. In the G-commerce model, the key is to determine the price of a resource at which supply equals demand, i.e., market equilibrium. Therefore, G-commerce adopts a specific scheme of pricing adjustments based upon the estimated demand functions. Commodities markets assume that all resources are identical within the market and that a market-wide price can be established that reflects the natural equilibrium between supply and demand. Some systems, such as G-commerce, have used such an approach to resource allocation – in their case CPU and disk for jobs. Unfortunately, as different providers naturally provide various levels of services, the assumption of equivalent resources is not a good fit for Storage@desk. Further, as Storage@desk exists in a dynamic environment which consists of a large number of distributed machines, it is difficult to adopt the G-commerce approach to analytically determine equilibrium based on supply and demand formulas. Storage Exchange [6] mimics the stock exchange model and builds a double auction model, in which providers and consumers submit their bids to buy and sell storage service. As the clearing algorithm is crucial in terms of utilization and profit, different algorithms have been investigated in Storage Exchange to meet various goals. In this chapter, we will focus on both the auction and posted price market models where prices or bids can be determined based on local information. The goal is to reduce the computation and communication cost, as well as to create a scalable algorithm in a distributed environment that consists of a large number of service providers and consumers.

13.3 Storage@desk

Before we present our storage market model, let us introduce Storage@desk [9] from two aspects, specifically the architecture and QoS model. In the last decade, scientific advances have enabled applications, sensors, and instruments to generate vast amount of information, which in turn creates an enormous demand for storage. We believe that desktop PCs represent a tremendous potential in the form of available storage space that can be utilized to relieve the increasing storage demand. To this end, we are developing Storage@desk to harness the vast amount of unused storage available on a large number of desktop machines and turn it into a useful resource for clients within a large organization. Storage@desk aggregates unused storage (disk) resources in an organization to provide virtual volumes accessible via a standard interface. The disk resources reside in a large number of hosts with different QoS properties, such as availability, reliability, performance, security, etc. SD clients can specify their QoS requirements (including size) and SD provides them with a volume that meets their requirements. The goal is to enable clients or client agents (storage consumers) to create virtual storage volumes with well-defined QoS requirement, accessible via the ubiquitous iSCSI standard [10] on top of storage resources on distributed machines (storage providers).

13.3.1 Architecture

Storage@desk, shown in Figure 13.1, has five “actors” in the architecture: clients that consume the virtual storage resources provided by Storage@desk, iSCSI servers that serve the clients’ requests, volume controllers that monitor and manage virtual volumes, storage machines (including pricing agents on them) that provide the physical storage resources, and one or more backend databases that store the system metadata. Clients interact with iSCSI servers via the iSCSI protocol, reading and writing blocks. Thus, client interaction is legacy based, requiring no code changes. The iSCSI layer is the main interface between the clients and administrators on the outside, and the Storage@desk services inside the system. It is a standards-based rendering of the SCSI protocol, but implemented over standard TCP/IP channels rather than a traditional SCSI bus. iSCSI servers implement the iSCSI protocol and interact with the database to acquire the block to storage machine mappings, with storage machines to read and write blocks, and with volume controllers to notify them of QoS warnings and errors. As client agents, volume controllers manage volumes on behalf of clients, mapping and remapping blocks to storage machines, ensuring proper replication, enforcing QoS characteristics, and responding to client hints about future use patterns. Storage machines interact with the database, keeping it updated with current QoS properties and available storage, with volume controllers that request block allocations, and with iSCSI servers that read and write blocks. On each storage machine, there exists a pricing agent that makes periodic adjustments to the local storage price. This agent will become the auctioning agent that holds the auction for the storage machine in the auction market model. Further, storage machines and iSCSI servers act as sensors that feed vital QoS information to both the volume controllers and the database. Finally, the database stores the information needed in the implementation. The database can be replicated and distributed to avoid becoming a hotspot.

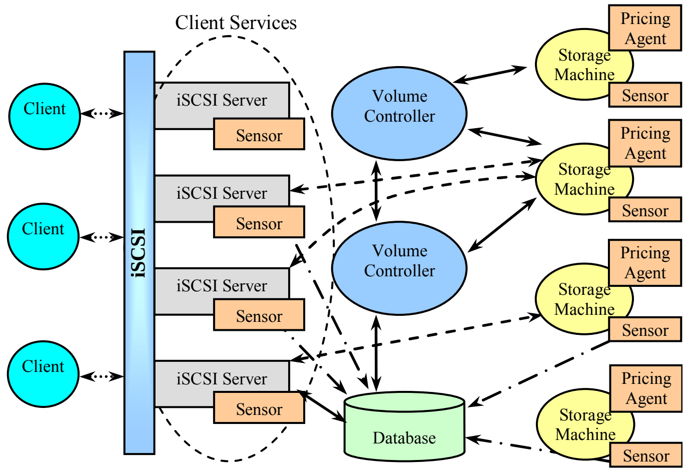


Figure 13.1. Architecture of the Storage@desk system. Clients interact with the system via an iSCSI interface (thus isolating them from the distributed nature of the resources behind the scenes). Arrows ⟶ indicate internal, Storage@desk volume control channels; Arrows ⋯➤ indicate the iSCSI operations from clients; Arrows - - ➤ indicate data interactions between iSCSI servers and machines; Arrows –·➤ indicate sensors pushing QoS data to the storage database

13.3.2 QoS Model

QoS is at the heart of Storage@desk. Storage@desk attempts to address the individual needs of its clients on a volume-by-volume basis. QoS is specified at volume creation and can also be updated throughout the volume's lifetime. For example, QoS may be changed to relax constraints that can no longer be met, to change budget or lifetime, etc. A client is free to change the QoS, which may become necessary when a client loses to others in a competition to a particular resource. We use a QoS vector Q =

[*A*, *B*, *C*, *D*, *R, S, W*] to represent seven QoS attributes, though we expect additions as work progresses.

- Availability (*A*): we define availability as the percentage of time that all bytes of a volume are accessible to the client. This value is calculated by dividing MTTF (mean time to failure) by the sum of MTTF and MTTR (mean time to repair). The specified value marks the minimum availability the client is willing to accept. Since this is from the client's perspective, volume controllers can create replicas, use erasure codes, and/or dynamically migrate blocks in order to mask failures from less available resources.
- Budget (*B*): we define budget as the virtual concurrency a client has to purchase raw storage resources for each budget period. This budget will be used over a period time of the storage volume. When a budget is exceeded, a client will have to drop the request and release the resource.
- Capacity (*C*): we define capacity as the total amount of storage the client desires in blocks. SD models raw storage as a number of blocks, whose sizes are fixed at the volume creation time.
- Duration (*D*): duration defines the lifetime of a volume.
- Reliability (*R*): we define reliability as the probability that no data within a volume will be permanently lost. This value defines the minimum reliability rate the client is willing to accept.

- Security (*S*): security is another QoS issue, and comes in many flavors and forms and various clients require differing levels of security. Some clients may require wire-level and storage-level data integrity guarantees while others may additionally require various privacy guarantees as well. Sometimes a volume may wish to prevent certain users from adding and removing blocks of data while other scenarios may allow for arbitrary addition of blocks of data, but limited deletion or replacement. Security can be addressed in all forms and at all stages in the Storage@desk system. Everything from storage level security, to wire-level security; from block level to volume level must be addressed. At a minimum Storage@desk will support specification of the level of privacy and data integrity required on target storage machines, the level of privacy and data integrity on the wire, and the acceptable methods for authenticating clients to storage machines for access.
- Write Semantics (*W*): we define write semantics as either WORM (write-once-read-many) or Write Many. These semantics can be important clues for efficiently implementing other QoS metrics. For example, by specifying that a volume is WORM, caching can be aggressively used for blocks already written.

Each QoS property defines the minimum level of service required by a client. In Storage@desk, it is the volume controller that will attempt to find resources to meet the client's minimum requirements subject to the budget of the client. The client can also specify a different QoS property to optimize – for example, maximizing availability.

Clients will configure Storage@desk volumes with QoS policy documents (similar to DESL documents) and may submit similar documents at various stages during a volume's lifetime for the purposes of providing hints to the system about more immediate scheduling decisions (such as how much data to pre-fetch into a block, etc.). Example 1~~Example 1~~ shows a sample of such a document. Note that the end client may not ever see a document of this form if proper UI tools are developed which translate more natural client requirements into requirements the system understands.

```
<volume id="672362D1-06A6-45db-B4E1-A77D0B3AB4E5">
	<name>UVa Volume</name>
	<owner>CN=Thomas Jefferson 1,E=jefferson@virginia.edu,OU=UVA Standard PKI User,O=University of Virginia,C=US</owner>
	<availability>99%</availability>
	<budget>1000</budget>
	<capacity>524288000 bytes</capacity>
	<duration>infinite</duration>
	<reliability>99.9%</reliability>
	<security>
			<storage>
			<privacy-level>encrypted</privacy-level>
			<integrity-level>checksum</integrity-level>
			</storage>
			<on-wire>
				<privacy-level>encrypted</privacy-level>
				<integrity-level>checksum</integrity-level>
			</on-wire>
			<authentication-mechanism>X.509</authentication-mechanism>
	  </security>
	  <performance allocation="50">
	     <read-write-ratio>2.5</read-write-ratio>
	     <coherence-window>5 minutes</coherence-window>
	   </performance>
	  <optimize>cost</optimize>
</volume>
```

Example 1: Illustrative document describing some QoS properties that a volume of storage might have. We have shown several different QoS properties, persistence, performance, availability, and integrity. Also included is an optional "allocation" for each. This indicates the relative importance the user attaches to different QoS elements.

13.4 Storage Market Model

In Storage@desk, competing independent clients or applications "purchase" storage resources from competing independent machines. In the auction market, storage machines hold auctions and solicit bids from a number of interested clients. At the beginning of the auction, each machine will announce the quantity of storage resources and history data on QoS properties. Because each client may receive bidding invitations from multiple storage machines, she will independently evaluate them and make a sealed bid to one machine. A bid includes quantity, and the price. Upon receiving bids, a storage machine will try to select a client that is willing to offer the highest price.

In the posted-price market, competing independent clients or applications purchase storage resources from competing independent machines. The model utilizes pricing agents to help storage providers determine the price for local resources. With the help of local search algorithms, pricing agents require no direct information of providers and consumers, which makes this approach very suitable for a grid environment. Thus, pricing agents only need to adjust resource prices periodically based upon locally observed consumer demand.

In both market models, the consumers are free to use their own strategies to choose from which provider to purchase. They, however, can't always get what they want due to the budget constraints. When two clients have the identical QoS requirement, the one with larger budget should have a better chance to meet the QoS. The use of a budget based system provides a mechanism to arbitrate between competing and likely conflicting clients and also provides a mechanism for system administrators to assign relative priorities between clients (or at least their purchasing power). We will use this market approach to produce a storage grid that can 1) achieve a relatively stable state; 2) fulfil client QoS when adequate budgets are available; and 3) degrades in accordance with relative budget amounts.

13.4.1 Assumptions

In the Storage@desk market model, we assume that the value, or relative worth, of a storage resource is ultimately determined by supply and demand. Traditionally, a market is said to be in equilibrium state when there is a perfect balance of supply and demand. In grid environment, as is often the case in real life, the balance is difficult to achieve and maintain because of the existence of unpredictable system dynamics. Therefore we choose to measure market dynamics by the degree to which the utilizations on storage machines fluctuate. The utilization of a storage machine is defined as the percentage of used resources. As we will see, when the utilization does not change widely, neither does the price. Thus, if few changes to resource allocation are needed, we say the system is in a stable state.

We assume that the storage consumers and providers are self-interested "individuals" driven by personal goals. Obviously, a storage consumer aims to purchase storage resources that are affordable within the budget and satisfy the QoS.

13.4.2 Virtual Volumes

Clients create virtual volumes each of which has a particular size and consists of a number of blocks. A client will need to buy a number of blocks in the market. Each block represents the capability of storing a fixed amount of data on a specific machine. It is important to emphasize that we differentiate the blocks in terms of quality. For instance, some blocks are considered to have better QoS because the underlying machines are highly available and reliable. While the same quantity of disk storage is provided, the blocks with better QoS properties should become more expensive for two reasons. First, it is fair to reward a provider for a better services rendered. Second, it will help the clients to tell a "good" block from a "bad" one, thus spend the budget efficiently and have better chance to achieve QoS goals.

For simplicity, we say that the market consists of a finite number S of blocks, distinguishable in terms of quality, from which a consumer may choose to create a virtual volume. We use R^S to denote the resource space. As a volume consists of a number of blocks, an allocation vector $x = [x_1, \ldots, x_S]$ can represent the blocks purchased by a consumer, where x is in R^S and a non-negative number x_i stands for the amount of the i-th blocks.

13.4.3 Storage Providers

A storage provider, as a storage machine, sells a number of blocks out of the available free disk space it has via some allocation policy, such as a fixed amount of dedicated storage, some percentage of currently unused storage, etc. Each storage machine is responsible for determining how many raw storage blocks it has to offer, for how long, and at what price (with the help of a pricing agent). All of the storage managed by a single storage machine is equivalent so that a storage machine simply has to determine and advertise the number of blocks available and a single price point for any of them. However, as we pointed out before, storage resources on two machines are not necessarily equivalent. For each storage machine, the revenue is calculated as the product of the price and the number of used blocks. There exists a software agent on each machine, which is called the auctioning agent in the auction market and the pricing agent in the posted-price market, respectively.

In the auction market, the auctioning agent will hold the auction for the resources on the storage machines. When the auction starts, the agent on the i-th machine sends the invitations to the potential interested buyers in the form of (y_i, q_i), where y_i represents the number of the blocks and q_i the history data on the QoS properties. A bid from the *j*-th machine can be represented as (x_j, p_j), where x_j represents the number of the blocks the machine needs and p_i the price willing to pay. It is important to note that x_j is less than or equal to y_i. When the auction ends, the agent will select the machine with the highest price and award the requested resources. In case there is a tie, the earliest bid wins. If there are more resources than what the machine needs, e.g., $y_i > x_j$ if the *j*-th machine wins, the agent will go through the buyer list in the descending order of their bidding price and repeat the selection process.

In the posted-price market, as each machine wants to maximize the revenue, the pricing agent will leverage the pricing power to affect the utilization and in turn the revenue. We will discuss the pricing algorithm in details in Section 13.4.5. We define a price vector $p = [p_1, \ldots, p_S]$ to represent the prices of the blocks, where p_i is the price of the *i*-th blocks. Once a client makes a purchase, this storage service will be rendered by the storage provider for a predefined period of time. It is the machine's job to make sure the blocks solely available to the client.

13.4.4 Storage Consumers

Storage consumers are volume controllers which clients use as their agents. Clients express their needs to volume controllers in the form of virtual volumes. Each volume is specified in the form of a QoS vector $q = [A, B, C, D, R]$. Clients allocate portions of their overall budget to each of their volumes and the volume controllers use this budget to purchase resources from storage machines. Acting on behalf of clients, volume controllers agree to buy blocks from storage machines to construct virtual volumes. Figure 13.2 shows the steps of resource allocation when clients want to create a volume. 1) Storage machines advertise their current price and QoS attributes. 2) Clients specify QoS and budget constraint. 3) Volume controllers retrieve machine information. 4) Volume controllers purchase blocks from a number of storage machines, and 5) construct a storage solution to meet the client-specific QoS criteria. 6) iSCSI servers serve client requests via iSCSI protocol. 7) Volume controllers monitor service, and 8) inform clients of up to date status on resource prices and the QoS properties.

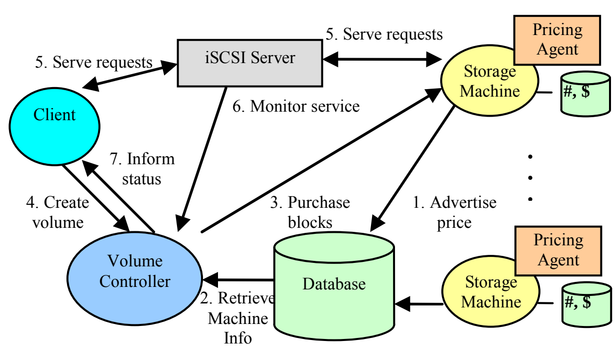


Figure 13.2. Logical resource allocation process

The allocation problem can be formalized as follows:

Given the resource space R^S and the price vector $p = [p_1, \ldots, p_S]$, a consumer would seek an allocation vector $x = [x_1, \ldots, x_S]$ for a volume with a QoS vector $q = [A, B, C, D, R]$, which can

1) Meet the budget constraint, i.e., $x * p <= B$;

2) Satisfy the QoS requirements, i.e., $q' >= q$, where q' is the vector of measured values.

It is up to volume controllers to choose simple or complex strategies to solve this problem. In this chapter, a volume controller follows a simple strategy in both the auction and posted-price market.

In the auction market, the controller can only submit a bid once in each bidding time period. In this research, we assume that the clients have high valuations, that is, they are willing to spend their entire budgets to secure the needed resources. It is never desirable for these clients to have nothing, because they need storage resources to hold their data. Thus, the clients will bid with the maximum prices within their budgets.

In the posted price market, pricing agents update prices and clients purchase storage on a regular basis, so clients may either stay put or opt to choose new machines to hold the volumes for the upcoming period. This decision process is affected by two questions: whether they have sufficient currency for the remaining time unit, and whether they have met or will have a better chance to meet the QoS. Given the answers to the questions, a client will try to move the volume's blocks to a less expensive machine if the budget becomes tight and to a machine with better QoS attributes if the volume QoS is not met. For example, a client has a QoS requirement for availability of 99.9%. Based on our observation in [11, 12], it is a reasonable approximation that a client needs to create three replications on different machines in order to achieve that goal. If a machine becomes less reliable, it may become necessary for the client to move the replica to a more reliable machine. If the budget becomes insufficient, the client may need to move a replica to a less expensive machine or reduce the number of replicas. It is possible that a client does not have sufficient budget to compete for "good" resources. As a result, the client has to make the trade-offs between various QoS criteria – including trade-offs between the amount of space one can get and the quality of the service one receives.

13.4.5 Storage Resource Pricing

At its heart, Storage@desk is a storage scavenging system that must deal with machines that are typically under the direct control of desktop users. Those machines often exist in an environment that is highly unstable and dynamic. This implies that those machines experience dramatic changes in load, disk usage, connectivity, uptime, etc. depending on the whims of the user sitting at the console. Additionally, administrative domains may enforce policy leading to large, coordinated downtimes and periods of unavailability. However, the chaotic nature of this environment should not prevent us from delivering reasonable level of QoS. Indeed, we believe that local search pricing agents will hold the most promise for Storage@desk. A local search pricing agent requires no assumption or knowledge of other providers and of the consumer population. Such an agent utilizes a local search algorithm that periodically adjusts the resource price based upon the demands observed in the previous and current time windows.

We choose to employ two classes of local search algorithms, greedy algorithm and derivative-following (DF) algorithms. A greedy pricing agent starts with a pre-defined price and makes small changes (increase or decrease) as long as the demand increases. Such an agent stops changing the price when it cannot see any improvement in demand. At this point, it is considered that a good price is found. Ideally, the price is close to the optimal value. The price moves in a small step δ, which is chosen randomly from a specified range; in the simulation we use a uniformly random distribution between 10% and 30%. We have found a random increment helps reduce the negative impacts from unpredicted dynamics in a distributed environment. Algorithm 1 lists the pseudocode of the greedy algorithm.

Algorithm 1: Greedy Pricing Algorithm

```
Set direction as UP or DOWN based on initial observations
FOR each time interval t_i (i >=2)  DO
     IF d_i >= d_i-1 THEN
            IF direction == UP THEN
             p_i  = p_i-1 * (1 + δ)
            ELSE
                      p_i  = p_i-1 * (1 - δ)
            END IF
     ELSE
            RETURN the price p_i
     END IF
END FOR
```

h when

there is no increase in demand. Rather, a DF agent will reverse the search direction at that point. A DF agent starts with a pre-defined price and changes the price in the same direction at each observation window until the most recent demand is observed to decrease from the demand in the previous window. In that case, the agent reverses the search direction and begins to make price changes in the other direction. When the demand again decreases the price movement will be reversed again. Therefore, the agent is able to track the changes in the observed demand and react fairly quickly to reverse the undesirable trend. In addition, it is very intuitive and requires only local knowledge. The latter makes it possible to develop a highly efficient solution in a grid, which involves a large number of distributed machines. Algorithm 2 lists the pseudocode of the derivative-following algorithm.

Algorithm 2: Derivative-Following Pricing Algorithm

```
FOR each time interval, t_i DO
    IF d_i > d_{i-1} THEN
        p_i = p_{i-1} * (1 + δ)
    ELSE IF d_i < d_{i-1} THEN
        p_i = p_{i-1} * (1 - δ)
    ELSE
        p_i = p_{i-1}
    END IF
END FOR
```

storage

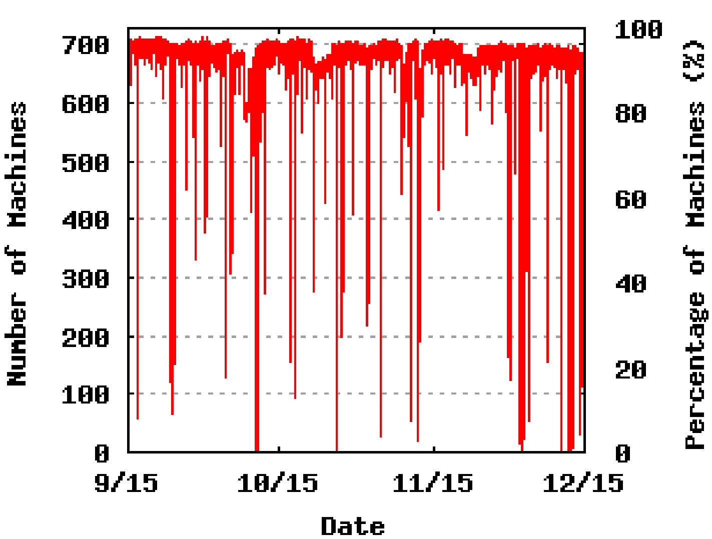
machine is only required to know the local demand. There is no need for a storage machine to know prices from others, although they may compete for consumers. Nor does a storage machine need to know demands from all consumers. Second, a storage machine is allowed to leverage independent pricing power to compete for positions in the market. Thus, rather than one price fits all, the market recognizes the quality differences between storage resources and enables prices to reflect those differences. Third, with the feedback price signals, a client is encouraged to make trade-offs among many QoS attributes and compose a service that maximizes QoS under a specific budget.

13.5 Evaluations

Using our market model, we want to provide two things with respect to availability and resource allocation. First, the overall resource allocation system and pricing performance in the system can be stable. Second, when resources are available, the resource allocation mechanism must perform efficiently and effectively – meaning that volume controllers make the proper decisions and can purchase the proper resources to meet their availability goals. Additionally, the resource allocation process should degrade such that it favors those who have allocated higher budgets to their storage when all other things are equal.

To evaluate our model, we construct a trace-driven simulation. In this simulation, we choose to study volume availability to demonstrate the effectiveness of our market model. We simulate our model using trace data, which we collected from 729 public machines in the classrooms, libraries, and laboratories at the University of Virginia. An analysis of this data has been published as a feasibility study of Storage@desk [9]. During a time period of three months in 2005, these public machines send to a central database a snapshot for each five-minute interval that contains statistics such as free disk space, CPU utilization, memory usage, etc. Figure 13.3 shows the number of available machines for each five-minute interval. Around 700 machines were reachable most of the time. There were several events where large number of machines went down due to network partition, power outage, and scheduled maintenance, etc., which are displayed as the downward spikes in the figure.

Figure 13.4 shows the number of machines categorized by their availabilities in terms of nines over the 10-week span. We use three-nine machines to represent the machine group whose availability is greater than 99.9%, two-nine machines for availability greater than 99%, and one-nine machines for availability greater than 90%. The majority of the machines had an availability of 2 nines or 3 nines. Although more than 500 machines started with 3 nines at the first week, their availabilities gradually decreased as the time went by. This was expected given the unreliable nature of machine usage on these desktops. At the same time, the number of one-nine and two-nine machines increased significantly. The population of zero-nine machines remained steady for 10 weeks. In the end, there were about 60 three-nine machines, 200 two-nine machines, 400 one-nine machines, and 75 zero-nine machines.



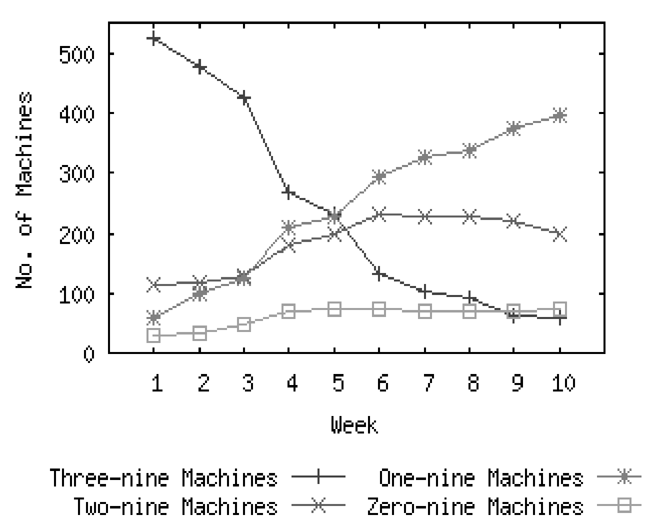


Figure 13.3. Number of available machines Figure 13.4. Machine counts by availability

Each volume is assigned with a budget of 100 (low budget), 200 (medium budget) and 300 (high budget), in a random, uniform distributed fashion. Also, a volume is randomly given an availability requirement of 1 nine, 2 nines and 3 nines. This assignment creates a good mix of various budgets and availabilities among the volumes. In our simulation, we assume that each volume consists of one block and each machine has 10 blocks available for Storage@desk, so each machine can hold up to 10 volumes.

Under a pre-defined budget and availability requirement, each client creates one volume by purchasing blocks and makes a number of replicas for the volume in order to satisfy the availability requirement. The number of replicas a client tries to make is determined by how many nines the client desires. For example, a client with a requirement of 3 nines will make three replicas of the volume. As we pointed out earlier, this is a reasonable choice given the fact that the majority of the machines have an availability of 90% or higher. We make sure that one machine will not hold two replicas of the same volume, so a client will distribute three copies on three different machines.

From the trace, we know the status of each machine, in other words, whether the machine is available, at every five-minute interval. A volume is available as long as there is at least one replica accessible, otherwise it is unavailable. Thus, we can easily obtain MTTF and MTTR for each volume, and compute its availability.

We simulate our model in two market settings, the over-supply and under-supply cases. Note that 729 storage machines can hold 7,290 volumes, which is the supply in the market. In the over-supply case, there are 3,500 clients, i.e., 3,500 volumes in the system, which consume 95% of supply if each volume makes 2 copies on average. Due to the budget constraints on some volumes, the actual consumption is much lower, about 76% at the beginning of the simulation as shown in Figure 13.7 (a). In the under-supply case, there are 4,500 clients demanding 120% of supply.

In the auction market, each storage machine will randomly solicit bids from 60 clients. In the posted-price market, storage machines set the initial price as $Price_{initial}$ = (*budget* / *demand*) / *duration*, where *budget* is the total amount of currency in the system at the beginning of the simulation, *demand* is the number of blocks needed by all the clients, and *duration* is the number of weeks in the simulation (10 weeks). We intentionally lower the initial price by 10% to create an initial leeway for customers with a tight budget.

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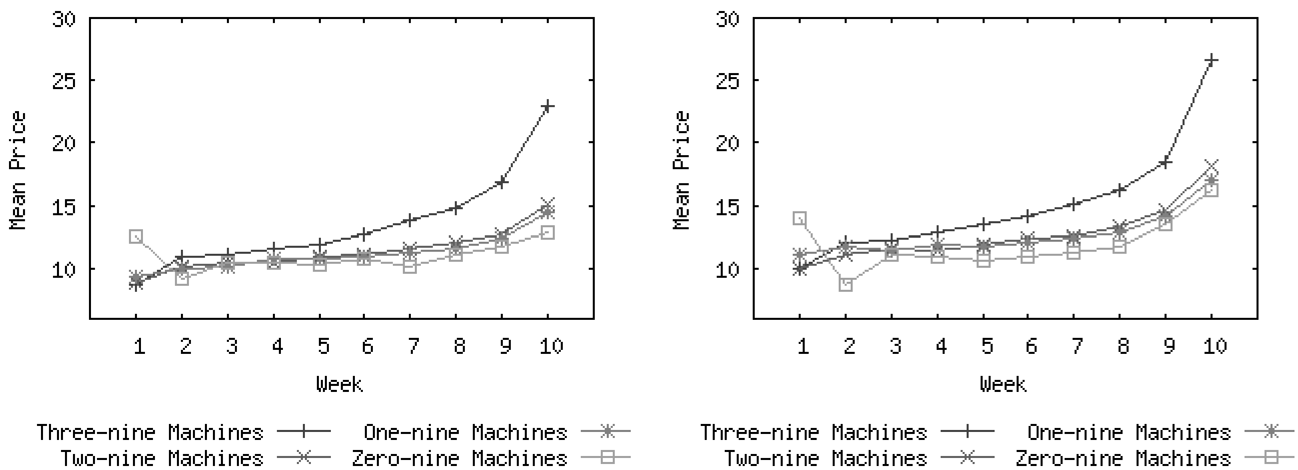
13.5.1 Price and Allocation Stability

In this section we study the mean price and mean utilization distributions under two demand scenarios. Figure 13.5 show the mean price distribution in the auction market model for the oversupply case (a) and the under-supply case (b). In both cases, while the prices increase slowly from week 2 to week 9 for machines have less than 3 nines, they jump in the end of the simulation. The weekly increase is significantly larger for three-nine machines. This is caused by the fact that the low-budget clients who do not have sufficient funds to win bids in the beginning of the simulation are able to afford good-quality machines later on. As we will see later, the posted-price market model can avoid this problem, as low-budget clients manages to purchase "cheap" resources from low-quality machines.

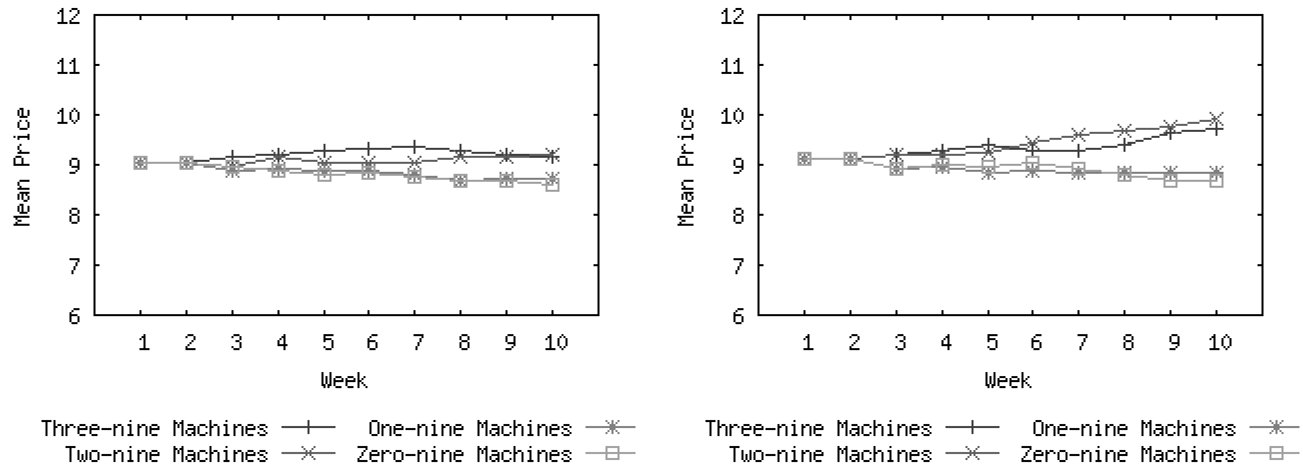


a) Over-supply case (b) Under-supply case

Figure 13.5. Auction - mean price distribution for 10 weeks

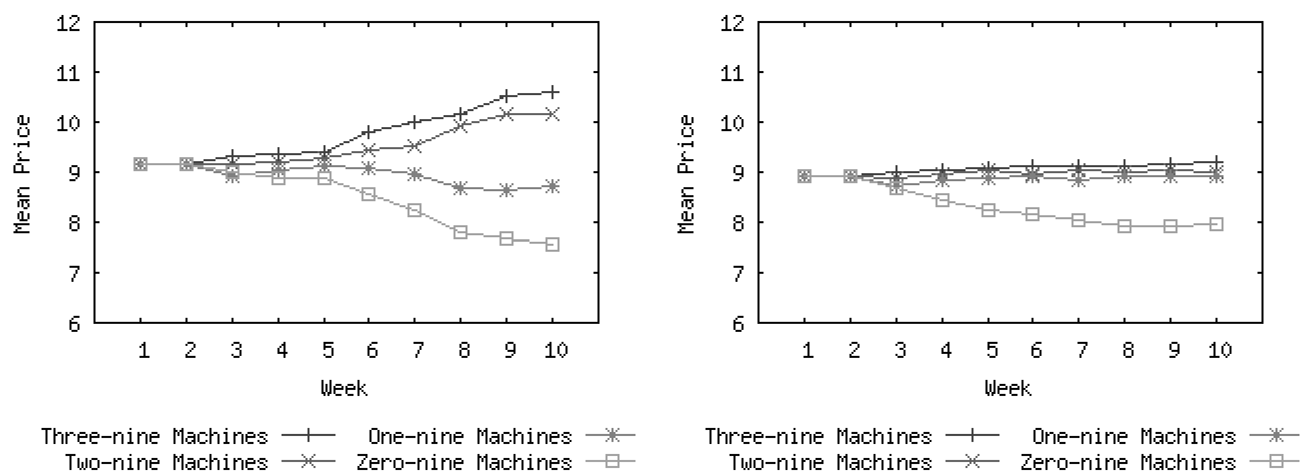
Now we will first look at how greedy pricing affects the price for the time period of 10 weeks. For the over-supply case (Figure 13.6 (a)), all machines start with the same initial price of 9.17, but begin to diverge in week 3. As the simulation continues, the clients begin to assess their volumes and resource allocations, and take appropriate actions based on perceived availabilities and the remaining budget. Subsequently, the machines with higher number of nines will see more demand from clients, while those with lower nines experience diminishing demands. So, machines with 2 or 3 nines begin to ask a higher price for its storage resources, while machines with 0 or 1 nine begin to ask for a lower price. As a result, two-nine machines have a price of about 7% higher than zero-nine machines. Since there are more two-nine machines, they have a better chance seeing higher demand than three-nine machines and thus have a higher price in the end of the simulation. For the under-supply case (Figure 13.6 (b)), the prices also diverge, but to a much smaller degree. The machine groups with lower nines will not experience a significant drop of client demands, since the demand exceeds the total supply in the system. The clients become less quality sensitive, and pay more attention to the quantity. As a result, machines with more than two nine have a very close mean price, so do machines with zero or one nine. And the price gap between two-nine machines and zero-nine machines becomes larger, about 15%, at Week 10.

Figure 13.7 illustrates the mean price distribution for derivative-following pricing for each of the four availability classes (base on the number of nines) over the 10-week study. For the over-supply case (Figure 13.7 (a)), all machines also start with the same initial price of 9.17, and begin to diverge in week 3 based on their availabilities. The price changes continue till week 8, where the prices reach a relatively stable level. At week 10, zero-nine machines have the lowest mean price of 7.55, while three-nine machines have the highest mean price of 10.60, or 40% higher. This gap is much bigger than the one when using greedy pricing. Also this time, three-nine machines have a slightly higher price than two-nine machines, reflecting the order of their availability. For the under-supply case (Figure 13.7 (b)), similar to what happens in greedy pricing, the prices diverges to a smaller degree. Machines with more than one nine have a very close mean price. And the price gap between three-nine machines and zero-nine machines becomes smaller, about 16%, at Week 10.



(a) Over-supply case (b) Under-supply case

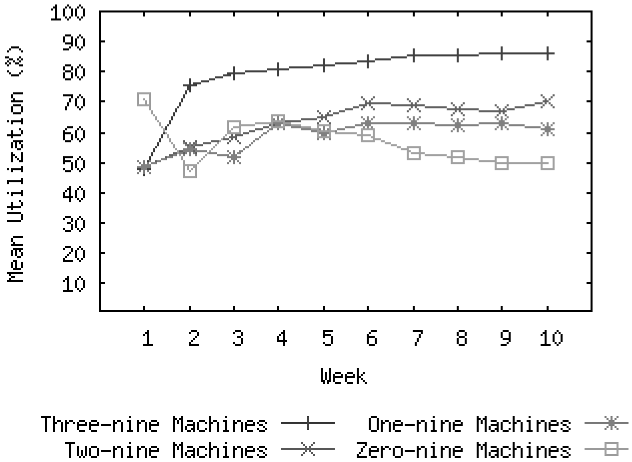
Figure 13.6. Greedy pricing - mean price distribution for 10 weeks



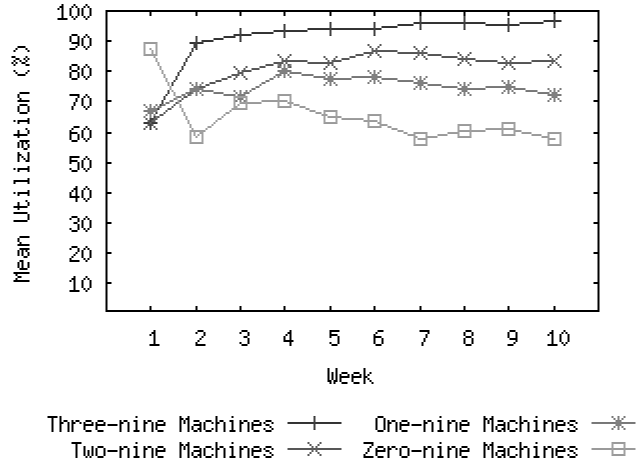
(a) Over-supply case (b) Under-supply case

Figure 13.7. Derivative-following pricing - mean price distribution for 10 weeks

The clients try to shy away from low available machines and pursue machines with high availability if the budget allows. Figure13.8 show the mean utilizations in the auction market. In the auction market, the three-nine machines at week 10 have a mean utilization of 86% and 97% in the over-supply and under-supply case, respectively. In contrast, the zero-nine machines at the week 10 have a mean utilization of 50% and 58% in the over-supply and under-supply case, respectively. The utilization in the posted-price market is higher as shown in Figure 13.9, because in this case clients can always get what they intend to purchase. In contrast, the clients who do not win bids in the auction market will not get another chance to purchase resources until next week. As both pricing algorithms have similar effects on resource utilization, we choose to only present derivative-following pricing here. For the over-supply case (Figure 13.9 (a)), three-nine machines start with 76% utilization and become close to fully utilized at week 8; on the other hand, zero-nine machines see the utilization decreases gradually till around 40% at week 7. For the under-supply case (Figure 13.9 (b)), machines with 2 or 3 nines quickly become fully utilized. The utilization on zero-nine machines and one-nine machines remains 82% and 94%, respectively, due to the overwhelming demand in the system.

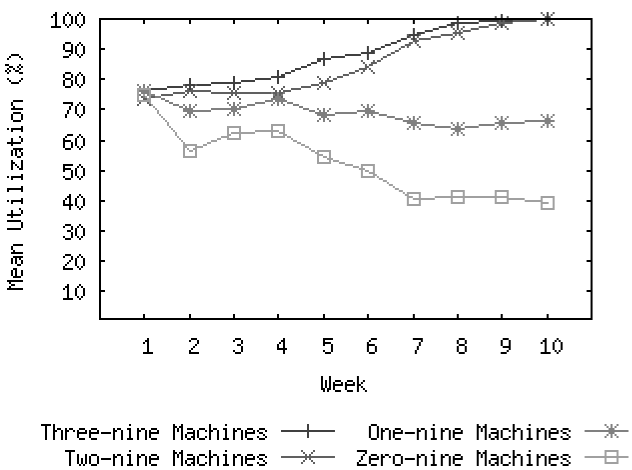


(a) Over-supply case

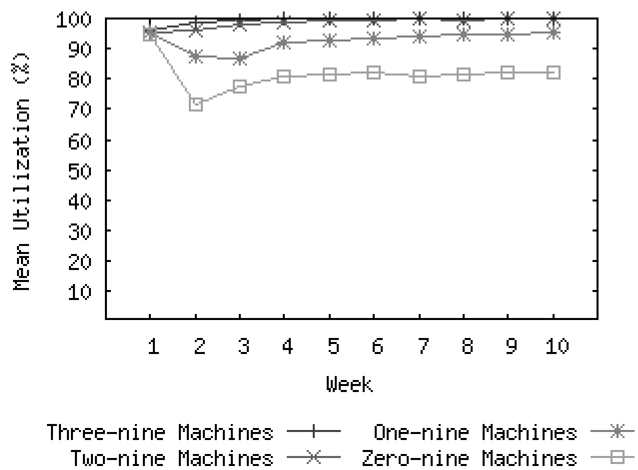


(b) Under-supply case

Figure 13.8. Auction - mean utilization distribution for 10 weeks



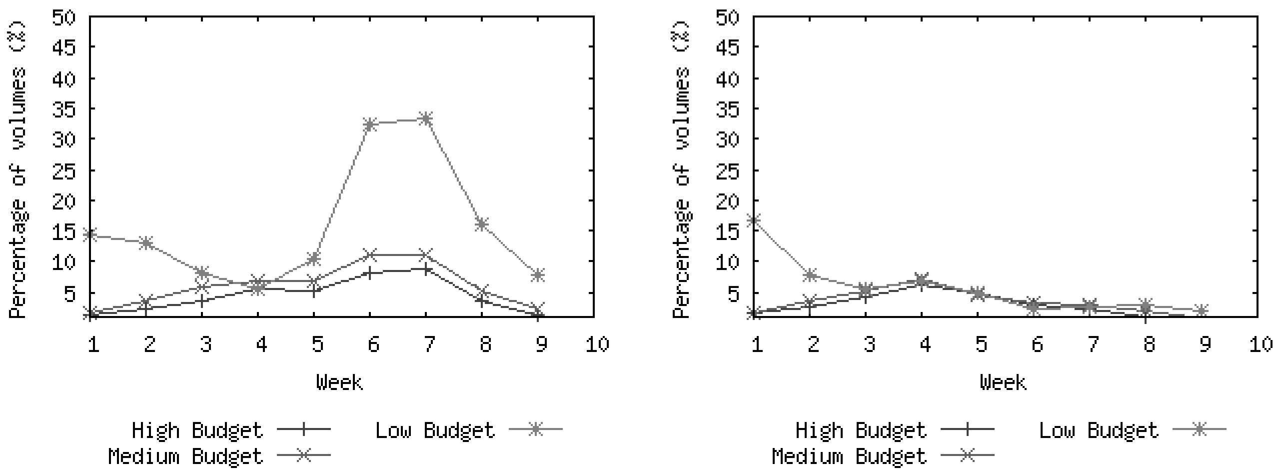
(a) Over-supply case



(b) Under-supply case

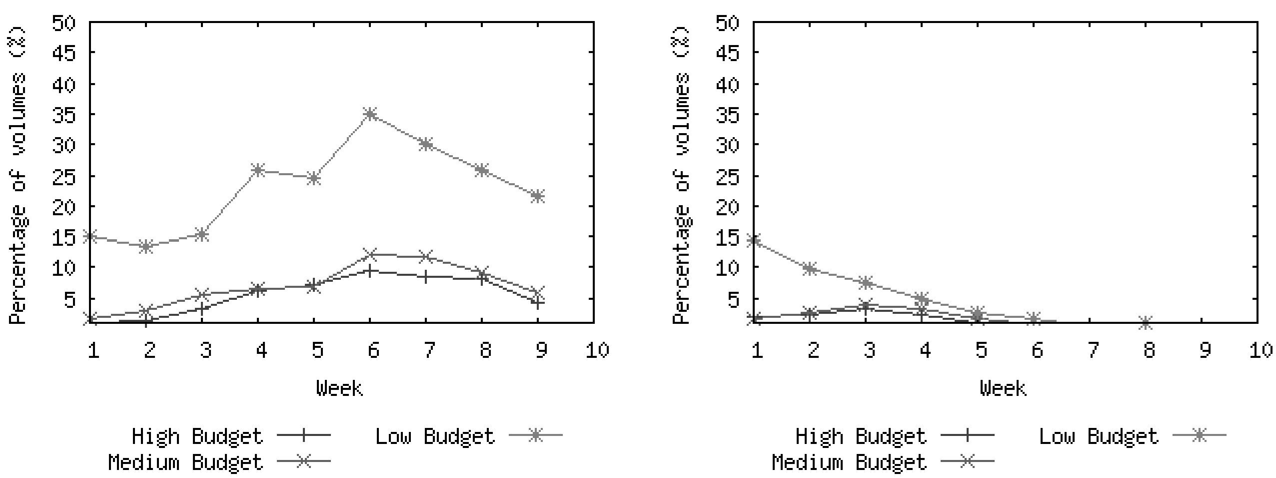
Figure 13.9. Derivative-following pricing - mean utilization distribution for 10 weeks

Figure 13.10 and 13.11 present volume migration rates in10 weeks for greedy pricing and derivative-following pricing respectively. We can see that, for both pricing algorithms, when volumes have a higher budget, less than 10% of them need to move their replicas at each week to improve their availabilities. Volumes with low budget migrant more frequently, because they have to consistently search for affordable resources as a result of competitions. For the under-supply case, very few volumes migrate due to the limited supply of resources.



(a) Over-supply case (b) Under-supply case

Figure 13.10. Greedy pricing - mean utilization distribution for 10 weeks



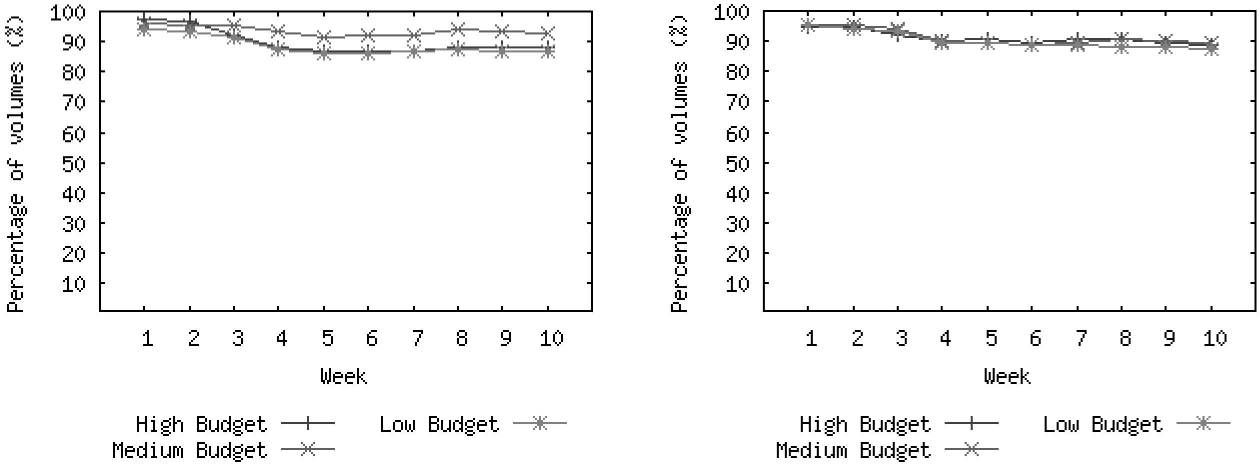
(a) Over-supply case (b) Under-supply case

Figure 13.11. Derivative-following pricing - mean utilization distribution for 10 weeks

For derivative-following pricing, 2,325 volumes, or 66.4%, do not migrate at all in the over-supply case, and 2,858 volumes, or 81.9%, migrate less than twice. In other words, the majority of the volumes are able to quickly find resources that can meet their availability requirements. In total the volumes perform 3,601 migrations over 10 weeks, of which 63% come from the low budget volume, 21% from the medium budget volume, and 16% from the high budget volume. This is expected because, while the high budget volumes can still afford good resources, some low budget volumes are forced to move as the price pressure increases. In the under-supply case, with limited supply, the market has no much room for the volumes to move around. As a result, 3,896 volumes, or 86.6%, do not migrate once, while 4,396 volumes, or 97.7%, migrate less than twice. Among 1,045 migrations from all the volumes, 64% come from the low budget volume, 20% from the medium budget volume, and 16% from the high budget volume. These numbers are quite close to those from the over-supply case. It indicates that the volumes with higher budgets do have a better chance to quickly find reliable resources and meet the availability. Therefore, we consider, in the over-supply case, the system becomes stable when the machines reach steady utilizations at week 8 and the clients with sufficient budgets complete the volume migrations. In the under-supply case, the large demand has already confined the market movements to a smaller window, thus the system becomes stable rather quickly when the machines remain steady utilizations since week 4.

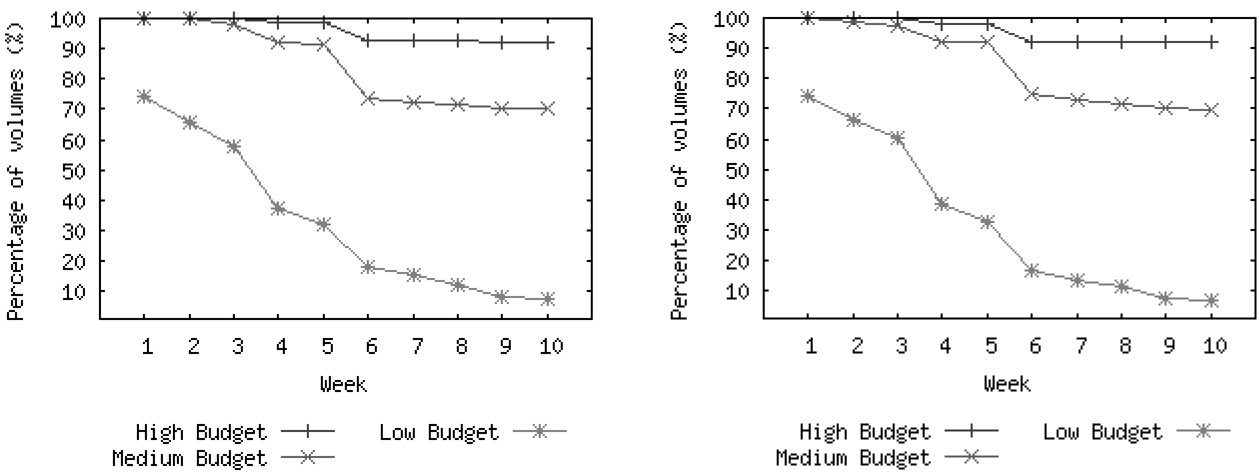
13.5.2 Meet Availability Goals and Adherence to Budgeted Priorities

For each client, the key is to meet the availability goal under the budget constraint. It is expected, to a high probability, a volume should be able to meet a relatively lower availability for a wide range of the budgets, because in this case a volume only needs a small number of replicas that can be done with a small budget. On the other hand, when a volume needs a high availability, the volume has to purchase a large quantity of storage resources for replicas. This can be difficult when the budget is limited. Therefore, there exists a contention for storage resources and the budget constraint will eventually affect the probability of a volume can meet the availability. As the posted-price market produces more stable prices and utilizations than the auction market, we will only show the results from the former in the section. In the posted-price market, both pricing algorithms can prioritize clients based on their budgets, and we will only present the results from derivative-following algorithm here. Figure 13.12 and 13.13 show the percentage of volumes that satisfy the availability of 1 nine and 3 nines, respectively. In each figure, (a) illustrates the over-supply case and (b) presents the under-supply case. From Figure 13.12, we can see that the budget plays a small role for one-nine volumes. In the over-supply case, 88% of high budget volumes meet the 1 nine availability at week 10, while 87% of low budget volumes do. This small difference becomes even smaller in the under-supply case. It indicates that low budget is sufficient for a volume that needs a low availability.



(a) Over-supply case (b) Under-supply case

Figure 13.12. Percentage of one-nine volumes that satisfy the availability



(a) Over-supply case (b) Under-supply case

Figure 13.13. Percentage of three-nine volumes that satisfy the availability

The situation changes when a volume has an availability of 2 nines. The chance for a low budget volume has 2 nines availability decreases from 87% at week 1 to 36% at week 10 in the over-supply case and from 87% to 33% in the under-supply case. In comparison, above 90% of the medium and high budget volumes still have a good chance to meet the availability requirements. In this case, the budget draws a clear distinction between low budget volumes and higher budget volumes, while medium and high budget still can be considered equivalent. The latter can no longer hold true as shown in Figure 13.11 when the volumes demands an availability of 3 nines, where each volume needs to purchase storage for three replicas. While about 92% of high budget volumes meet the goal at week 10, the percentage for medium budget volumes and low budget volumes drop to 70% and 8% in the over-supply case, and 70% and 7% in the under-supply case. In summary, the system is able to achieve, in both cases, a partial ordering of client QoS fulfilment matching client budget ordering, which clearly serves the purpose of the budget constraint. This should encourage clients to make trade-offs between resource price and various QoS attributes.

13.6 Future Research Directions

This study enhances our understanding of how market approach helps with storage resource allocation in a new storage grid. However, much remains to be learned about the agent behavior and market model in Storage@desk.

- We will take computing and network resources into considerations to give our model a higher level of realism. This will inevitably introduce new research challenges. When a client purchases various resources from multiple providers, it needs to carefully make a purchase plan ahead of time in order to coordinate the consumption of different resources at the desirable time.

- We will explore new QoS properties, e.g., security and performance, and support them in our market model. Their impacts on resource management can be two-fold. First, like the previous problem of multiple resource purchase, a client need to make a good plan in order to simultaneously achieve multiple QoS properties. It may come to a time when it is not possible to achieve all desired QoS properties. At that time the client has to prioritize one or more most important properties. Second, we plan to research other possible pricing algorithms, e.g., based on genetic algorithm or ant colony algorithm.
- We will introduce the concept of penalty to the market. A penalty will be assessed when a resource provider cannot meet its pre-specified QoS level. For example, for a resource provider advertising an available of 99.9%, it needs to pay a certain amount of penalty for the time periods that it did not provide a three-nine service. This will provide an incentive for providers to honestly announce the quality of their services.

13.7 Conclusion

In this chapter, we present a market-based resource allocation model for Storage@desk, a new storage grid where software agents determine local prices for resource providers based on the derivative-following algorithm. We describe both the auction market model and the posted-price market model in the Storage@desk architecture. We use a trace-based simulation to evaluate both models and show that the posted-price market model is able to produce a more stable market with higher utilization.

In the posted-price market, once the price, quantity, and quality of storage resources are advertised, storage consumers can choose from which providers to buy, and how many. With the help of the volume controller, a client can make trade-offs among many QoS attributes and compose a service that achieves the desirable QoS under a specific budget. A good resource allocation can be achieved by the cooperation from two sides: providers adjust prices for their resources in accordance with the demand they experience, while consumers adjust their allocation as reacts to the QoS experienced and the price changes based on the amount of currency left in the budget.

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