

DISTRIBUTED PROCESSOR ALLOCATION ALGORITHMS

A THESIS

SUBMITTED ON THE FIRST DAY OF MAY, 1998

TO THE DEPARTMENT OF ELECTRICAL ENGINEERING AND COMPUTER SCIENCE

OF THE SCHOOL OF ENGINEERING OF

TULANE UNIVERSITY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF

MASTERS OF SCIENCE IN COMPUTER SCIENCE

BY

Joshua S. Allen

APPROVED:

Dr. Mark Benard

Dr. Bill Buckles

Dr. Boumediene Belkhouche

© Copyright 1998

by

Joshua S. Allen

All rights reserved.

Acknowledgements

I would like to thank several people for their role in this thesis. First and foremost is my advisor, Dr. Mark Benard, for helping me over the past two years with this task. Dr. Benard has offered me great advice and most certainly this paper would be in chaos without his help.

Without my friends I never would have made it to this point in my life. Wendy, Lily, Valerie, Mark, Amanda, Sean, Pat, Erik, and countless others who have been there for me – I love all of you more than you can imagine. You have all made my life better in many ways. Life would not be nearly as fun without you.

Thanks goes out to Erik Schaffer for teaching me `zsh` scripting. You helped me to automate much of my data generation and it made my life much easier.

I also thank my family, Mom, Dad, and Matt, for more support than a person could ask for. I am the person I am today because of them, and I could not have made it where I am without their love and support. Dad and Mom have been very strong influences in my life, and I appreciate all of their support, emotional and financial, over the past 23 years of my life. I cannot imagine being such a strong person without them.

Finally, I thank Jim for everything he has done for me. He is the most loving, most sensitive, and most intelligent person I have ever met. The past two years have been the best in my life, and I cannot imagine life any other way.

Abstract

A processor allocation algorithm is a method to determine the best processor within a distributed system on which to run a process. For example, assume a machine X with one processor and a high load average. The user of machine X creates a new process. However, since its load average is so high, machine X decides to offload the process to another machine Y . Hence, a processor allocation algorithm is invoked to determine the best processor Y . The goal of a processor allocation algorithm is to do this automatically, completely transparent to the user.

An alteration of the aforementioned approach is to allow processes to migrate dynamically even after they have started executing. This is achieved via preemptive scheduling with the use of check-pointing (saving and transmitting process state), whereas the former approach is achieved via non-preemptive scheduling (process runs to completion on the machine where it is started).

This research looks at three different processor allocation algorithms, one centralized and two distributed. All three algorithms were implemented using kali-scheme, a distributed version of scheme48 [CJK95]. Three environments were used to test the algorithms: simulation, quasi-simulation, and full implementation. Test cases highlighting performance, scalability, and fault tolerance were run to compare and contrast the algorithms.

Contents

Acknowledgements	ii
Abstract	iii
1 Introduction	1
2 Background	4
2.1 Description and Definitions	4
2.2 Classifications	7
2.3 Issues	7
2.4 Approaches – Previous Work	8
2.4.1 Centralized Up-Down Algorithm [ML87]	8
2.4.2 A Hierarchical Algorithm [WT80]	10
2.4.3 A Microeconomic Algorithm [FYN88]	11
2.4.4 Decentralized Load Sharing in Condor [LLM88]	11
2.4.5 Theimer and Lantz Approaches [TL88]	12
2.4.6 Random Probe Sets [ELZ86]	14
2.4.7 Stumm Approach [Stu88]	14
2.4.8 Distributed Load Balancing using a Local Process Queue [HJ87]	14
2.4.9 Receiver Initiated Distributed Heuristic Algorithm [Tan95]	15
2.4.10 Dynamic Scheduling in Shared-Memory Multiprocessors [HL96]	16

3	Objectives and Criteria	17
3.1	Objective	17
3.2	Algorithms	19
3.2.1	Token based Algorithm	19
3.2.2	Distributed Q-learning Algorithm	20
3.2.3	Centralized Algorithm	21
3.3	Criteria	22
3.3.1	Quantification of Criteria	23
3.3.2	Metrics	25
3.4	Issues	25
3.4.1	Location policy	25
3.4.2	Selection policy	26
3.4.3	Preemption versus non-preemption	26
3.4.4	Testing	27
4	Implementation	28
4.1	Environment	28
4.2	System Architecture	30
4.3	Load Average Computation	31
4.4	Fault tolerance	31
4.5	Messaging	33
4.6	Processes	35
4.7	Randomness	36
4.8	Process Migration	36
4.9	User controlled variables	36
4.10	Logging and Statistics	37

4.11	Selection policy	38
4.12	Transfer policy	39
4.13	Location policy	39
4.14	Placement and Migration Thresholds	39
5	Testing and Results	42
5.1	System Variables	42
5.2	Test Cases	44
5.3	Results	47
5.3.1	Process Creation Request Hop Counts	47
5.3.2	Number of Messages Generated per Algorithm	49
5.3.3	Process Creation Interval	54
5.3.4	Location of Process Creation	56
5.3.5	Scalability	57
5.3.6	Environment	60
5.4	Analysis	63
5.4.1	Environment	63
5.4.2	Process Type	65
5.4.3	Load Averages near the end of execution	65
5.4.4	Algorithms	66
6	Conclusions	67
6.1	Transparency	67
6.2	Flexibility	68
6.3	Reliability	69
6.4	Performance	69
6.5	Scalability	69

6.6	Future Work	70
6.6.1	Algorithms	70
6.6.2	Analysis/Testing	71
6.7	Implications	71
A	Test Cases	74
	Bibliography	99
	Biography	100

List of Figures

2.1	Centralized Usage Table Algorithm	9
2.2	Hierarchical Algorithm	10
3.1	Token based Algorithm	18
3.2	Distributed Q-learning Algorithm	20
4.1	Load Average Algorithm: Calculates the load average every 5 seconds for the past 1, 5, and 15 minutes.	32
4.2	Processor selection algorithm	40
5.1	Hop Counts for Q-learning Algorithm	48
5.2	Messages Generated for Q-learning Algorithm	50
5.3	Messages Generated for Centralized Algorithm	52
5.4	Messages Generated for Token-based Algorithm	53
5.5	Comparison of Process Creation Interval	55
5.6	Comparison of Process Creation Location	56
5.7	Algorithm scalability	58
5.8	Algorithm scalability. Data shown for test A	59
5.9	Environment stats. Data shown for cpu-intensive processes	60
5.10	Environment stats. Data shown for highly-interactive processes.	61
5.11	Environment stats. Data shown for disk-intensive processes.	62
5.12	Environment stats. Data shown for a mix of all process types.	63

A.1	Q-learning Algorithm – simulated environment – Test Case A – Iteration 1 – Load Averages over Time	74
A.2	Q-learning Algorithm – simulated environment – Test Case A – Iteration 1 – Maximum Unfairness over Time	75
A.3	Q-learning Algorithm – simulated environment – Test Case A – Iteration 1 – Standard Deviation of Loads over Time	75
A.4	Q-learning Algorithm – quasi-simulated environment – Test Case A – Iteration 1 – Load Averages over Time	76
A.5	Q-learning Algorithm – quasi-simulated environment – Test Case A – Iteration 1 – Maximum Unfairness over Time	76
A.6	Q-learning Algorithm – quasi-simulated environment – Test Case A – Iteration 1 – Standard Deviation of Loads over Time	77
A.7	Q-learning Algorithm – quasi-simulated environment – Test Case B – Iteration 1 – Load Averages over Time	77
A.8	Q-learning Algorithm – quasi-simulated environment – Test Case B – Iteration 1 – Maximum Unfairness over Time	78
A.9	Q-learning Algorithm – quasi-simulated environment – Test Case B – Iteration 1 – Standard Deviation of Loads over Time	78
A.10	Q-learning Algorithm – quasi-simulated environment – Test Case C – Iteration 1 – Load Averages over Time	79
A.11	Q-learning Algorithm – quasi-simulated environment – Test Case C – Iteration 1 – Maximum Unfairness over Time	79
A.12	Q-learning Algorithm – quasi-simulated environment – Test Case C – Iteration 1 – Standard Deviation of Loads over Time	80
A.13	Q-learning Algorithm – quasi-simulated environment – Test Case D – Iteration 1 – Load Averages over Time	80

A.14 Q-learning Algorithm – quasi-simulated environment – Test Case D – Iteration 1	
– Maximum Unfairness over Time	81
A.15 Q-learning Algorithm – quasi-simulated environment – Test Case D – Iteration 1	
– Standard Deviation of Loads over Time	81
A.16 Q-learning Algorithm – Full implementation – Test Case A – Iteration 1 – Load	
Averages over Time	82
A.17 Q-learning Algorithm – Full implementation – Test Case A – Iteration 1 –	
Maximum Unfairness over Time	82
A.18 Q-learning Algorithm – Full implementation – Test Case A – Iteration 1 –	
Standard Deviation of Loads over Time	83
A.19 Q-learning Algorithm – Full implementation – Test Case C – Iteration 1 – Load	
Averages over Time	83
A.20 Q-learning Algorithm – Full implementation – Test Case C – Iteration 1 –	
Maximum Unfairness over Time	84
A.21 Q-learning Algorithm – Full implementation – Test Case C – Iteration 1 –	
Standard Deviation of Loads over Time	84
A.22 Q-learning Algorithm – Full implementation – Test Case D – Iteration 1 – Load	
Averages over Time	85
A.23 Q-learning Algorithm – Full implementation – Test Case D – Iteration 1 –	
Maximum Unfairness over Time	85
A.24 Q-learning Algorithm – Full implementation – Test Case D – Iteration 1 –	
Standard Deviation of Loads over Time	86
A.25 Token-based Algorithm – quasi-simulated environment – Test Case A – Iteration	
1 – Load Averages over Time	86
A.26 Token-based Algorithm – quasi-simulated environment – Test Case B – Iteration	
1 – Load Averages over Time	87

A.27 Token-based Algorithm – quasi-simulated environment – Test Case C – Iteration	
1 – Load Averages over Time	87
A.28 Token-based Algorithm – quasi-simulated environment – Test Case D – Iteration	
1 – Load Averages over Time	88
A.29 Token-based Algorithm – Full implementation – Test Case A – Iteration 1 – Load	
Averages over Time	88
A.30 Token-based Algorithm – Full implementation – Test Case B – Iteration 1 – Load	
Averages over Time	89
A.31 Token-based Algorithm – Full implementation – Test Case C – Iteration 1 – Load	
Averages over Time	89
A.32 Token-based Algorithm – Full implementation – Test Case D – Iteration 1 – Load	
Averages over Time	90
A.33 Centralized Algorithm – quasi-simulated environment – Test Case A – Iteration	
1 – Load Averages over Time	90
A.34 Centralized Algorithm – quasi-simulated environment – Test Case B – Iteration	
1 – Load Averages over Time	91
A.35 Centralized Algorithm – quasi-simulated environment – Test Case C – Iteration	
1 – Load Averages over Time	91
A.36 Centralized Algorithm – quasi-simulated environment – Test Case D – Iteration	
1 – Load Averages over Time	92
A.37 Centralized Algorithm – Full implementation – Test Case A – Iteration 1 – Load	
Averages over Time	92
A.38 Centralized Algorithm – Full implementation – Test Case B – Iteration 1 – Load	
Averages over Time	93
A.39 Centralized Algorithm – Full implementation – Test Case C – Iteration 1 – Load	
Averages over Time	93

A.40 Centralized Algorithm – Full implementation – Test Case D – Iteration 1 – Load	
Averages over Time	94
A.41 Q-learning Algorithm – Quasi-simulated environment – Test Case : Longer	
Creation Interval – Iteration 1 – Load Averages over Time	94
A.42 Q-learning Algorithm – Quasi-simulated environment – Test Case : Test Same	
Creation Location – Iteration 1 – Load Averages over Time	95
A.43 Token-based Algorithm – Quasi-simulated environment – Test Case : Longer	
Creation Interval – Iteration 1 – Load Averages over Time	95
A.44 Token-based Algorithm – Quasi-simulated environment – Test Case : Test Same	
Creation Location – Iteration 1 – Load Averages over Time	96
A.45 Centralized Algorithm – Quasi-simulated environment – Test Case : Longer	
Creation Interval – Iteration 1 – Load Averages over Time	96
A.46 Centralized Algorithm – Quasi-simulated environment – Test Case : Test Same	
Creation Location – Iteration 1 – Load Averages over Time	97

Chapter 1

Introduction

As microcomputers and networks have become more prevalent over the past twenty years, high expectations in the area of distributed computing have evolved. In the past, computing was very centralized. For example, in the era of mainframes, computing was all performed in one large central computer. Later as microcomputers became popular, people used their personal computers to do the same type of computing, but in an isolated environment. Soon after, network technology allowed these isolated personal computers to connect to one another. Users were aware of the network and decided how to use it.

The flaw with the aforementioned approach is the lack of transparency. Computer users are aware that they are connected to a network and they must know certain things about it in order to use it. The goal of distributed systems is to allow users to operate on a personal workstation but with all of the advantages of working on a mainframe computer and to do so transparently.

Several examples exist of how the network transparently transforms a collection of computers into a single unit. One example is a network file system. Sun Microsystems's Network File System (NFS) allows users to access the same directory structure and same files no matter which workstation they happen to be currently using. Without a network file system, users are

left to manually making copies or moving their own files between computers every time they change workstations. This unfortunately is the approach many people still take.

Another example of how a distributed system transparently increases productivity is a mail server. With a mail server users can check their e-mail on any computer in the system and have the same consistent view of their mailboxes. A user can send e-mail to a user at a system instead of a user at a computer. Then, no matter which computer a person actually uses, s/he receives the email. If email is sent to a user at a particular computer, the system can be robust enough to forward the mail to the mail server. Therefore, the system functions as a single unit even when users recognize a specific component.

A third aspect of a distributed system and the focus of this thesis is processor allocation. Suppose that there is an idle workstation on the network and that your computer currently is running very slowly. If you could offload one or more of your processes to the idle machine, then you could perform more work in a shorter amount of time. The goal of a processor allocation algorithm is to do this automatically, without the knowledge and/or consent of the user.

Suppose we were to implement the above example. In order to offload a process to another processor, we must have a way of determining which processor should run the process. A processor allocation algorithm is just that, a way of determining the best processor within the distributed system to which to give a process.

Other than automatically offloading processes within a distributed system, another use of a processor allocation algorithm could be in a distributed implementation of the UNIX utility `top`. Processor allocation can also be used in databases to submit queries to the most appropriate machine in a collection of back-end servers. In the business world, distributed processor allocation algorithms could be used to assign tasks of a project to employees.

This research looks at three different processor allocation algorithms, one centralized and two distributed. All three algorithms were implemented using `kali-scheme`, a distributed version of `scheme48` [CJK95]. Three environments were used to test the algorithms: simulation,

quasi-simulation, and full implementation. Test cases highlighting performance, scalability, and fault tolerance were run to compare and contrast the algorithms.

Chapter 2

Background

2.1 Description and Definitions

A processor allocation algorithm is a method to determine the best processor within a distributed system on which to run a process. For example, assume a machine X with one processor and a high load average. The user of machine X creates a new process. However, since its load average is so high, machine X decides to offload the process to another machine Y. Hence, a processor allocation algorithm is invoked to determine the best processor Y. The goal of a processor allocation algorithm is to do this automatically, completely transparent to the user.

An alteration of the aforementioned approach is to allow processes to migrate dynamically even after they have started executing. This is achieved via preemptive scheduling with the use of check-pointing (saving and transmitting process state), whereas the former approach is achieved via non-preemptive scheduling (process runs to completion on the machine where it is started).

In order to achieve processor allocation, several steps must be taken.

- Determination of when to offload a process, **transfer policy**. A simple way to determine this is to use a threshold to compare against the load average. Whenever the load average goes above a certain threshold, a processor decides to offload a process, either new ones as

they come into the system or by migrating existing jobs. A more complex approach is to offload processes based upon user preferences and past experiences. For instance, a user may indicate, via preferences, to the operating system to offload new processes whenever the new jobs are batch jobs, such as compilations or ray-tracing. However, the user may decide always to run highly interactive jobs locally. Even better, the system could monitor performances of jobs over time and use that history of information in deciding when to offload jobs.

- Collection of state information from the distributed system. **(Definition) Global**

Knowledge: “The interpretation of information from the set of physically distributed sources which are needed by a distributed algorithm” [CK87]. We refer to the collection of global knowledge as **information policy**. In order to obtain global knowledge, information must be collected from the system via the network. Many different approaches exist for this stage of processor allocation. There are centralized and distributed approaches, many of which are discussed in section 2.4. The goal of this stage is to collect the most accurate and up-to-date information from the system as possible with the least amount of network communication. Unfortunately, the two are directly proportional, so as accuracy and timeliness of information increase so does network communication. Two questions raised by this algorithm include (1) What information should be collected? (2) How should the information be collected?

- Selection of the best job to transfer, also known as **selection policy**. This algorithm is invoked after the system has decided to transfer a job as concluded by the transfer policy. Again, the system can decide simply only to offload newly incoming jobs. If the system is designed to migrate running processes, then a more complex selection mechanism is needed, perhaps based upon user preferences or past experience as previously discussed.
- Selection of a processor on which to run a process, otherwise known as **location policy**. A simple approach is to pick the machine with the lowest known load to accept the new

process. However, a better selection mechanism is often needed, one that incorporates other factors such as amount of free memory and swap space, the overhead of transferring a job to the remote machine, and the speed and architecture of a processor. The goals in selecting the best processor are to minimize response and execution times.

- **Transferral of a task to the remote machine.** For a new job, this might involve simply spawning a process remotely. With a shared file system and remote execution facilities, this is very simple. However, if the process needs to use local resources such as display, keyboard, or mouse, this becomes more complicated because the process cannot simply execute on the remote machine; a communication mechanism must be in place in order for the process running remotely to use local resources. To further complicate matters, whenever a process is preempted and migrated to remote machine, its state information must be saved and transferred to the remote machine so that it can continue running where it left off. Mechanisms to perform this are known as check-pointing.

The following definitions are useful when discussing distributed processor allocation:

- **(Definition) Load Sharing (LS):** Attempts to ensure that no processors are idle while processes wait for execution [KL88].
- **(Definition) Load Balancing (LB):** Attempts to equalize all work performed in a distributed system [KL88].
- **(Definition) Global Objectives:** “Functional goals of a distributed algorithm which are defined on the state of the entire distributed system.” [CK87]

This thesis focuses on information policy and location policy. The other topics are addressed but simple and direct solutions are used as opposed to more robust ones.

2.2 Classifications

Algorithms used to manage a distributed system can be classified in the following ways, as described by [CK87]:

- Centralized or Distributed: A centralized algorithm runs on a single machine whereas a distributed algorithm runs on many machines concurrently.
- Dynamic or Static: A static processor allocation algorithm determines processor allocation in advance whereas a dynamic one makes decisions on the fly at run time. A static algorithm might be based on logical partitioning or statistics [ELZ86].
- Cooperative or Selfish: A cooperative algorithm shares information with others in order to achieve a common goal. A selfish algorithm works alone without communication in order to obtain its goal [FYN88].
- Optimal or Suboptimal: An optimal algorithm is one which attempts to produce the best results all of the time. A suboptimal algorithm might produce the best results but it is not guaranteed to. It might choose the best known option given a limited amount of knowledge.

2.3 Issues

Issues associated with processor allocation are abundant. For instance, how should the CPU load be determined such that it gives an accurate measurement for all CPU's in terms of whether they can handle more processes. Several approaches exist, including measuring the number of processes in the ready state or averaging the number of processes to go through the run state over a predetermined amount of time.

Should the algorithm be centralized or distributed? The easiest ideas are centralized; however, these centralized algorithms have unfortunate side effects, such as single point of failure, communication bottleneck, and inability to scale well. Distributed algorithms offer

disadvantages as well, such as potential overhead (communication and processing across the system) and less knowledge of the system (i.e., global knowledge, definition 2.1). Overall, distributed algorithms are more appealing because they are more scalable and avoid single points of failure.

Other issues include the overhead of running processes on a remote processor as opposed to running processes locally. How is this overhead measured and how can it be used in the decisions of whether to run the process locally or remotely? How can stability be achieved so that all processors are given equal amounts of work? How can network communication be reduced?

An issue associated with processor selection is how much information to collect from the network. [ELZ86] claims that little information is needed to gain nearly optimal performance. However, there is much information available from which to choose, such as load average, total amount of memory, amount of free memory, information about the process to be run, processor speed, processor architecture, and paging rate.

2.4 Approaches – Previous Work

2.4.1 Centralized Up-Down Algorithm [ML87]

A centralized approach to processor allocation uses a coordinator to keep an up-to-date usage table (see figure 2.1). This usage table keeps track of how busy each processor within the distributed system is. To do so, each processor is assigned a number in the usage table. A positive number indicates that a machine has performed work for a remote computer. A negative number indicates that a machine has processes waiting to run.

Whenever a processor becomes free, it notifies the coordinator. The coordinator checks its usage table to determine which processor has the lowest usage value. This indicates the machine that has been waiting the longest to offload a process(es). The processor that has become free gets a process from the chosen machine and runs it.

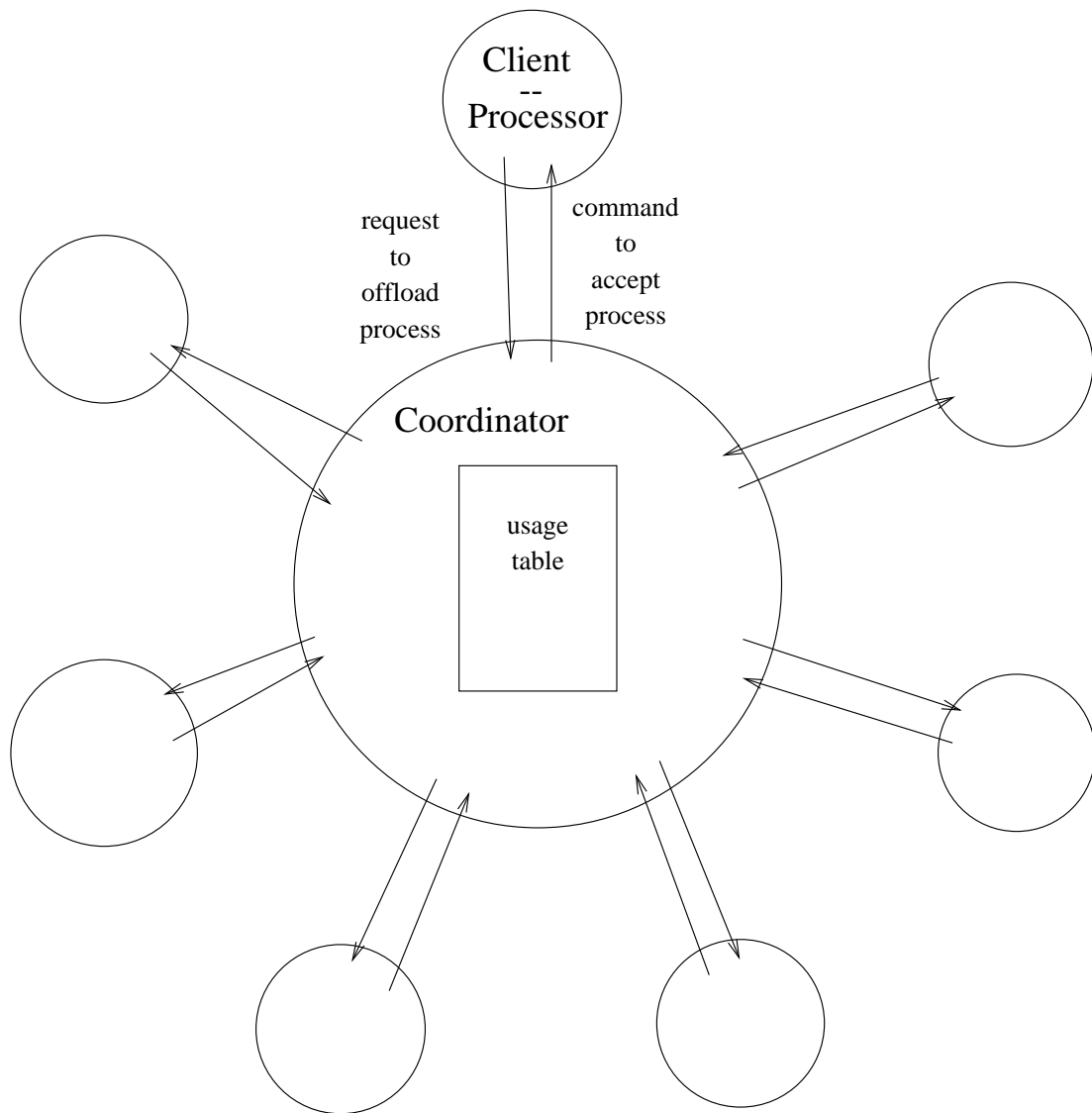


Figure 2.1: Centralized processor allocation algorithm: A coordinator accepts requests from processors to offload jobs. When a processor becomes free, the coordinator determines the machine with the lowest usage value and a process is migrated from the chosen machine to the processor that has become free.

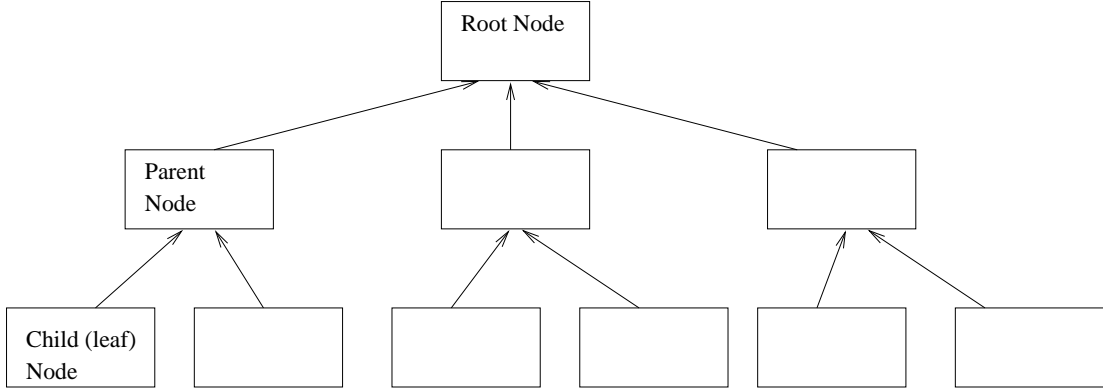


Figure 2.2: Hierarchical processor allocation algorithm: The parent of a node is a supervisor. All work requests are given to the direct supervisor. If a processor under that parent is free, the supervisor gives it to that processor. Otherwise, the process is handed to that supervisor's supervisor until a free processor is found or the root of the tree is reached. Upon reaching the root of the tree, a request is queued until a processor becomes available.

If a processor is not doing remote computation, then its value in the usage table is decremented slowly over time until it reaches zero or requests or performs remote work.

This centralized approach carries with it many of the advantages and disadvantages associated with all centralized algorithms. However, it is a very fair approach to processor allocation in that it tries to distributed work equally.

2.4.2 A Hierarchical Algorithm [WT80]

A hierarchical algorithm (see figure 2.2) for processor allocation works as follows: All processors are set up in a virtual hierarchy (tree structure), such that some processors are workers and others are supervisors. Supervisors also have supervisors until the root of the tree is reached. The way the algorithm works is as follows.

When a request for work is generated, that request is sent to the immediate supervisor. If the supervisor has enough free workers to perform the request, then the supervisor allocates the work to those workers. If not, the supervisor sends the request to his supervisor. This process continues until a supervisor who receives the request has enough free processors to allocate the work. If the request reaches the root supervisor and no processors (workers) are available, then the root supervisor holds the request until a worker becomes available.

Fault tolerance in this approach can also be provided. If a supervisor fails, then a worker for that supervisor is promoted to the supervisor position.

2.4.3 A Microeconomic Algorithm [FYN88]

Another distributed approach to processor allocation is one based upon the concepts of microeconomics. This approach is modeled after an economy. Competition sets prices for resources (e.g., the CPU). Jobs compete for resources by issuing bids and resource allocation is made through auctions.

In this approach resources and jobs are viewed as agents. Each agent has a goal and rules to follow in order to achieve its goal. Each agent attempts to achieve its goal without cooperating with any other agent. Effective global allocation of jobs is achieved indirectly through selfish competition (Invisible Hand).

When a job enters the system, it is given an initial amount of money. Whenever it migrates through the system it must pay to cross a link. It must also pay for CPU time. Processors sell CPU time and communication bandwidth, and they set their own prices. A processor's goal is to maximize revenue. In order to get information on the prices of remote resources, processors advertise on Bulletin Boards of adjacent processors. Based upon current pricing information, amount of money remaining, and resource demands, jobs attempt to purchase resources and to be serviced.

Whenever a processor becomes idle, it holds an auction for resources. If local prices change a processor may send an advertisement to its neighbor processors.

2.4.4 Decentralized Load Sharing in Condor [LLM88]

A distributed system named Condor currently uses a decentralized load sharing algorithm [HS97]. Its algorithm is unique in two ways. (1) A processor broadcasts its load information using a region-change approach. In other words, processor information is broadcast only when there is a significant change and it is only broadcast to a select number of workstations. (2) Task

collision, the situation where many jobs are sent to a single station simultaneously, is avoided by using a preferred list approach.

The preferred list is defined as follows: “A workstation is the k^{th} preferred workstation of one and only one other workstation, where k is an integer.” and “If workstation i is the k^{th} preferred node of workstation j , then workstation j is the k^{th} preferred node of workstation i .” Using a preferred list, the probability of more than one workstation sending their jobs to the same workstation is very low and transferred tasks are evenly distributed.

A CPU is available for remote computation only if the keyboard is idle, the CPU is idle, it can handle the job requirements, and no other remote task is currently running on it. In the implementation, these requirements are translated to the following numbers: the average load ≤ 0.3 , the keyboard is idle > 15 minutes, and no remote task is currently running.

A processor is chosen based upon its priority. The priority of a workstation is incremented by the number of individual users with tasks queued on that workstation. The priority is decremented with the number of tasks submitted to that workstation and currently running (either remotely or locally). The workstation with the highest priority is contacted and requested to run the job. If swap space is sufficient, it accepts, otherwise the request goes to the next highest priority processor. If no processor accepts the job, it runs locally.

2.4.5 Theimer and Lantz Approaches [TL88]

Theimer and Lantz offer two approaches for processor allocation. One approach is centralized and the other is distributed. In the centralized approach, clients periodically send status information to a central server, and all remote execution requests go through that same server. Instead of all clients sending status information to the server and being included in processor allocation decisions, only those clients with a load below a certain threshold participate. The group of machines that do send requests to the server are known as host selection candidates.

The use of host selection candidates reduces the amount of network communication considerably and allows the algorithm to scale well. In simulations, Theimer and Lantz showed

that their centralized approach could work well with up to 1600 machines in the system. They also provided fault tolerance in the following way: At least k entities monitor the server to detect failure. Whenever the server fails, a new instance of the server is reconstructed by multi-casting a request for immediate state update. This approach to fault tolerance introduces a delay in service if a failure does occur since server reconstruction takes time.

Another approach to fault tolerance is to use $k + 1$ replicas of the server in order to survive k failures. Multi-casting provides a simple and cheap way of updating multiple copies of the server.

The second processor allocation approach offered by Theimer and Lantz is a decentralized scheduler, which they claim to be less complex but also less scalable than their centralized approach. In their decentralized approach, each client performs its own host selection (location policy). Only those clients needing to perform a host selection gather information from the system. When a client does collect information, it sends a request by multi-casting a query to those machines containing idle resources. How the client knows which machines are idle was not addressed by Theimer and Lantz.

The client receives replies from all willing candidate machines and the client selects the best candidate. The problem encountered by this approach is the large number of messages generated, $O(n^2)$ (where n is the number of machines), and the large number of replies received almost simultaneously. In order to cut down on network traffic, a client waits for only the first m replies, where m is user definable. Replying machines place a weight on a random delay before sending their replies. The weight is determined by how good a candidate machine thinks it is for accepting a remote execution request. This approach gives non-optimal but good selection as opposed to their centralized implementation.

The Theimer and Lantz approaches assume efficient broadcast and multi-cast communication and that the cost of multi-casting to non-recipient machines is negligible or none. Theimer and Lantz also assume that nearly all of the processes in their system are either short-lived or interactive.

2.4.6 Random Probe Sets [ELZ86]

Eager, Lazowska, and Zahorjan discuss a random probe set approach to processor allocation. Whenever a new job is created, the local machine load is compared to some threshold. If the local machine load is less than the threshold, then the new job runs locally. Otherwise, the task can be forwarded to remote machines, up to some fixed number of forwards (in order to prevent thrashing). Remote servers are chosen by probing a small random set of machines for load. Surprisingly, this approach performs quite well under simulation.

The goal of Eager, Lazowska, and Zahorjan was to achieve improved performance in a distributed system with as little information as possible. The two extremes for information gathering are no information gathering and complete information gathering. [ELZ86] chose to gather little information by randomly probing a small set of machines whenever offloading needed to occur.

2.4.7 Stumm Approach [Stu88]

The Stumm approach is based on server machines advertising their load, rather than clients querying for load averages. Advertising requires $O(n)$ messages, whereas querying generates $O(n^2)$ messages, where n is the number of machines in the systems.

However, hosts must always keep track of global state information. New hosts must wait for update messages from other machines before they can offload jobs.

2.4.8 Distributed Load Balancing using a Local Process Queue [HJ87]

Hac and Jin perform dynamic load balancing using a decentralized approach. Lightly loaded processors search for heavily loaded processors. Each processor dynamically calculates a threshold $T = \text{trunc}(\frac{\text{Number of Active Processes on all remote machines}}{\text{Number of remote processors}})$. Each processor also has a value C = maximum number of active processes allowed. This prevents the system from being overloaded.

The algorithm consists of three routines: The Local Process Queue Routine monitors for new jobs. When a new job is created, it is placed on the end of the local job queue if the Number of active processes $> C$. Otherwise, the job executes immediately.

The Local Monitor Routine runs whenever the local process queue becomes empty. It searches for the most heavily loaded machine (the one with the longest queue) and obtains the first job from that local process queue. Semaphores are provided to prevent two processors from obtaining the same job simultaneously.

The Distributed Monitor Routine broadcasts load information to other machines in the system. If a processor becomes saturated (i.e., Number of jobs in local process queue $> C$), it can suspend the distributed monitor routine until its load falls.

This system was tested under simulation using three types of processes: CPU-intensive, I/O-intensive, and CPU-I/O-intensive. Performance was measured by mean response time compared to the number of processors in the system.

2.4.9 Receiver Initiated Distributed Heuristic Algorithm [Tan95]

In this approach, whenever a workstation determines that it needs more work (e.g., its load average is below some threshold), it advertises that it needs more work. To do so, it selects another machine within the distributed system at random and then requests work from that machine. If the machine gives it work, then the requesting workstation performs it. Otherwise, it picks another machine at random from which to request work.

The requesting workstation continues to request work until it finds it or until it polls n machines. After polling these n machines, it stops polling for a certain amount of time or until it gets more work locally.

2.4.10 Dynamic Scheduling in Shared-Memory Multiprocessors

[HL96]

A common approach to load balancing (scheduling) in a shared-memory environment is to place all new jobs in a shared queue. Whenever a processor becomes idle, it allocates work to itself from the shared queue. According to Hamidzadeh and Lilja in [HL96], this approach requires a lot of overhead in accessing the shared queue and directly increases the overall execution time. They offer an alternative approach.

Hamidzadeh and Lilja try to minimize memory delay in process execution by considering locality of memory references. The name of their approach is SADS (Self Adjusting Dynamic Scheduling). One processor performs a branch and bound algorithm to compute scheduling based on loads of other processors and memory locality information. SADS searches through all partial and complete searches using a heuristic. There is also a depth-bounded version of SADS.

When SADS completes its dynamic scheduling, it places jobs in local queues of processors. To improve performance and reduce wait time, SADS performs its partial scheduling in repeated scheduling periods, self-adjusting the amount of time allocated to each scheduling period to minimize idle times.

Chapter 3

Objectives and Criteria

3.1 Objective

Given a collection of processors, each of which can receive external job requests, fair processor allocation should be performed for newly incoming jobs. In the case of dynamic process migration, fair processor allocation should occur during the lifetime of processes. Since the goal of the algorithm is to load balance, the unfairness at time t can be measured by the maximum difference in jobs between two processors. The performance of an allocation method over a time period can be measured by the average unfairness over that time period.

The goal of this research was to design and implement three processor allocation algorithms, one centralized and two distributed. Each algorithm is explained in detail in section 3.2. Three environments were implemented for these algorithms: simulation, quasi-simulation, and a full implementation. Performance criteria and test cases were developed and are used to compare the three algorithms and the three environments.

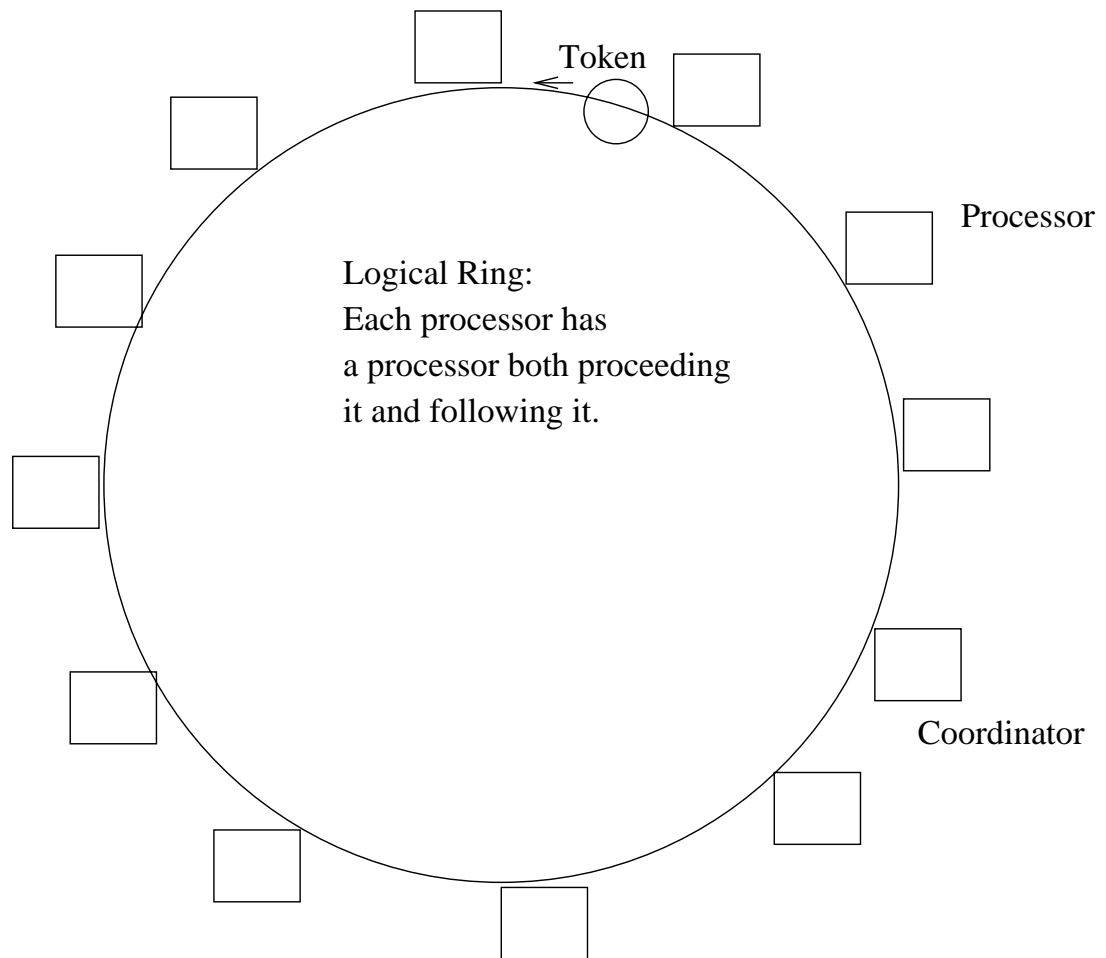


Figure 3.1: Token based processor allocation algorithm: A usage table containing current load and memory usage information in a token circulates around a logical ring of processors, updating information as it circulates.

3.2 Algorithms

3.2.1 Token based Algorithm

At startup, a logical ring is constructed, where each node in the ring represents a processor in the distributed system. A coordinator is then elected using an election algorithm. A single packet (the token) is then transmitted by the coordinator with an entry for each processor in the system. The entry contains the following information for each machine: load and amount of free memory.

Each time a machine receives the token, it does the following things:

1. The machine updates the token's usage table with its current load and amount of free memory.
2. If the machine wants to offload a process, it picks the machine with the lowest load that has enough free memory, and migrates the process to that machine.
3. The machine forwards the token to the next machine in the logical ring.

For fault tolerance, ring and token management procedures are implemented. A coordinator is elected at startup. The coordinator monitors for lost and duplicate token. If a token is duplicated, the coordinator removes one of the tokens from the ring. If a token is lost, the coordinator generates a new token. Other members in the ring monitor for coordinator failure. If the coordinator fails, then a new coordinator is elected.

When a new job is introduced to the system, the originating machine sets a timeout (adjustable by the user) for when the process is to be accepted. If the process has not been accepted by the timeout, then the originating machine broadcasts a message to other members of the ring to see if they are alive. If a machine does not respond, then it is assumed to have failed and it is removed from the ring. The process can be resubmitted to the system, ensuring at least once execution semantics. See figure 3.1.

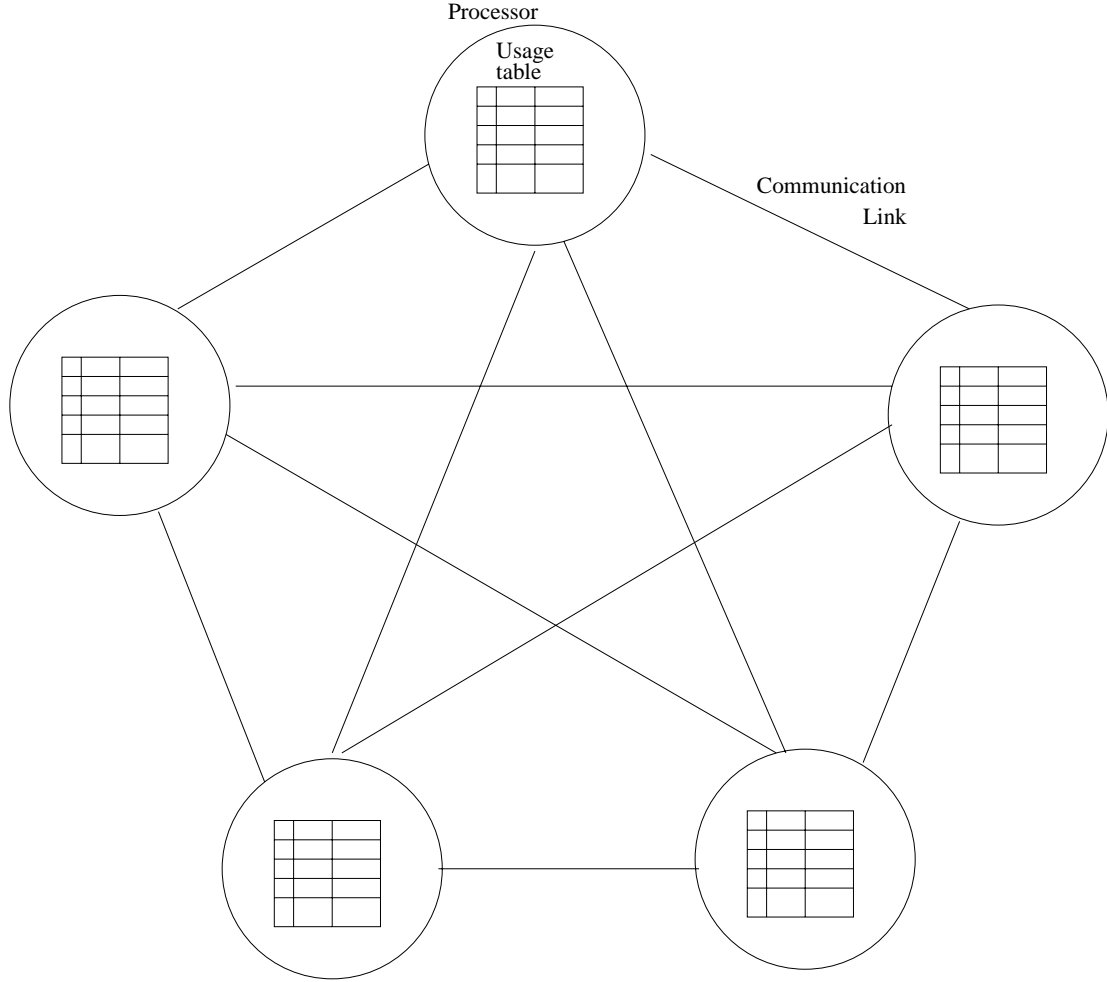


Figure 3.2: Distributed Q-learning processor allocation algorithm. Each processor maintains a usage table. Based upon this usage table, a processor can offload a process to any other processor in the system.

3.2.2 Distributed Q-learning Algorithm

Each machine maintains a table comprised of values reflecting the last known load on each machine. Initially, all values are zero (neutral). When a new job is introduced to a processor, that processor allocates the job to some processor in the system, perhaps itself. This choice is based on the table most of the time and made randomly the rest of the time (defined by parameter p , which is an integer between 0 and 100). Parameter p is used as a percentage. For example, if parameter p is 25, then processor selection will be made randomly 25% of the time and based upon a table the other 75% of the time.

The table is updated in the following way: When processor A chooses to give a job to processor B , A sends a request to B , which includes A 's current load. B updates its table using this information and decides whether to accept the job or forward the request to another machine. Ultimately, some machine C accepts the request and obtains the job from A .

Each machine (A through C) updates its usage table using load information passed to it in the request message, which is appended to the request as it is forwarded to each machine. A naive update rule is simply to replace old data with new data. However, a better approach might be to use weighted average of the old and new data, perhaps incorporating the age of the old data.

The only way a job could bounce around the system indefinitely is for new jobs to be introduced to the system faster than the system can send messages back and forth between machines. This is highly unlikely, thus in practice there is no indefinite postponement of jobs, although theoretically it is possible. To ensure that indefinite postponement does not occur, a hop count limit (implemented as the size of the distributed system + 1) is imposed. A machine receiving a request message with the hop count limit surpassed is forced to accept the process.

For fault tolerance, machines can be dynamically added and removed from the system. The system also detects failures of processors by using timeouts on process creation requests. When a new job is introduced to the system, the originating machine sets a timeout (adjustable by the user) for when the process has been accepted. If the process has not been accepted by the timeout, then the originating machine broadcasts a message to other members of the system to see if they are alive. If a machine does not respond, then it is assumed to have failed and it is removed from the local usage table. The process can be resubmitted to the system. This ensures at least once execution semantics. See figure 3.2.

3.2.3 Centralized Algorithm

For comparison reasons, a modified version of the Mutka/Livny up-down algorithm was implemented. In this centralized algorithm, all process creation requests go through a single

machine, although they can still originate anywhere. When a process is offloaded to a machine by the coordinator, that machine must return its reply that it has accepted the process. The same is true when the process finishes. Hence, the coordinator always knows (within time ϵ , defined to be the amount of time for a client to respond to the coordinator) when a remote machine is executing a process.

In the Mutka/Livny up-down algorithm, processes wait until a processor becomes free before they start executing. In this modified version, there is no notion of a processor being busy. All processes are offloaded immediately when they are created. Therefore, a processor's usage value does not get decremented for waiting-to-run processes. Hence, usage values are always zero or higher.

Whenever, a process is offloaded, the coordinator checks its usage table to determine which processor it deems to have the lowest load. The process is then migrated to that processor for execution. While the process is running, the processor running it accumulates a usage point every m seconds. If a processor is running n processes, it accumulates n usage points every m seconds. While a processor remains idle, its usage value is decremented by 1 usage point every m seconds until the usage value reaches zero.

3.3 Criteria

In general, distributed systems can be compared using the following criteria [Tan95]. Distributed processor allocation is no exception.

- Transparency

The distributed system should provide services such that the user is unaware of where within the system that the services take place. The system should function, at least from the user's perspective, as a single unit.

- Flexibility

The distributed system should be designed in such a way that it is easily changeable and customizable.

- Reliability

The distributed system should provide consistency and should function even in the presence of failures when possible. In other words the distributed system should be fault tolerant. When possible, failures should go unnoticed by the user.

- Performance

The distributed system should provide a reasonable and consistent response time to users and in general the system should provide a level of performance not less than that of a stand-alone machine. In other words, the distributed system should not penalize performance, and when possible it should enhance it.

[CK87] defines performance of a distributed algorithm as the “...degree to which an algorithm achieves its global objective.” Efficiency is described as the “...measure of the costs associated with [the] level of goal achievement.”

- Scalability

The design of a distributed system should be such that it functions appropriately and efficiently no matter how many machines comprise it.

- Security

The distributed system should prevent access to the system, including its processes, data, and services, from unauthorized users. Furthermore, individual users should be protected from other users in the same system.

3.3.1 Quantification of Criteria

In order to effectively compare and contrast algorithms, it is useful to quantify criteria. In this way algorithms can be compared using numbers and statistics rather than just words.

Several measurable statistics come to mind when measuring the **performance** of a processor allocation algorithm:

- Maximizing CPU utilization – the comparison of the load averages of all processors over time.
- Minimizing response time – the time elapse from process creation to process execution.
- Minimizing total elapsed time a process requires to finish – the time elapse from process creation to process termination.
- CPU overhead – a ratio of the amount of CPU time used by the processor allocation algorithm to the total amount of CPU time available.
- Network bandwidth overhead – a ratio of the amount of communication required by the processor allocation algorithm to the total network bandwidth.
- [KL88] states the goal of its scheduling policy is to meet users' performance expectations, which is centered on quality of service provided to jobs a user starts. Two measurable criteria used in this approach are response time and response ratio. Response time is defined to be the total amount of time a process resides in the system, whereas response ratio is the response time per unit of service.

Scalability can be measured by comparing the results of performance measurements of the algorithms running variable sizes of distributed systems. A good way to quantify scalability is to show total execution time of n processes in a system with m processors.

Fault Tolerance can be determined by introducing failures into the distributed and accessing whether the system continues to perform. If so, then how the performance level is effected is an interesting statistic.

Flexibility is not something that can easily be measured and hence a descriptive explanation of the features that make an algorithm flexible will need to be discussed, such a modularity, ease of use, etc.

Transparency also is difficult to measure, so again a descriptive explanation of why and how an algorithm is transparent will be given.

Security is not addressed in this thesis.

3.3.2 Metrics

Metrics are classified into three categories: message statistics, processor statistics, and process statistics. Message statistics include the number of each type of message generated and the sizes of each type of message generated. Averages and standard deviations can be computed for these.

Process statistics include the response time (time from creation to initial execution), the hop count of request messages for a process before it is accepted, and the total time a process resides in the system. For scalability comparisons, the total execution time of n processes in a system with m processors is also shown.

Processor statistics show the load average of processors over time as well as the average load and standard deviation.

There are a large number of other statistics that can be tracked and used to compare processor allocation algorithms. Due to the human inability to compare an overwhelming amount of information, a small set of statistics is preferable to a large set. However, it is important that this small set of statistics represents the major aspects of performance comparisons.

3.4 Issues

3.4.1 Location policy

Load alone may not be enough to determine the best processor on which to offload a process. From a user point of view, a distributed system should offer better or equal performance as compared to a stand-alone machine. Hence, criteria such as time delay between process creation

and initial execution is important. Items that would effect this include hop count of messages in the network, whether a binary needs to be migrated across the network, etc.

Another important variable to check when offloading processes is the amount of free physical memory. If a machine does not have enough free memory to run a new process then it would be pointless to try running it there. However, memory requirements of a process are rarely known before runtime. Still, if a machine has little free physical memory, performance might be effected due to swapping. Hence, many factors other than load might need to be taken into account when determining the best machine on which to offload a process and when comparing the performance of processor allocation algorithms.

Location policy depends highly upon the type of job being transferred. For CPU-intensive job, load alone is a good indicator. However, for disk-intensive jobs, the number of blocks read and written, and the location of file servers for files opened by a process are a large determinant of location policy.

3.4.2 Selection policy

The threshold of the selection policy is the point at which migration or placement begins. Threshold selection can be either dynamic or static. [PTS88] discusses a dynamic approach to threshold selection. The algorithms implemented here use a static approach as discussed in section 4.14.

3.4.3 Preemption versus non-preemption

According to [KL88], preemptive scheduling can increase the performance of a distributed system. However, preemption is difficult to implement because process state must be captured and transferred across the network in order for a process to resume where it was preempted. Also, one must determine when to it is more efficient to migrate an already running process rather than to let it finish execution where it currently runs.

Logic dictates there are at least several factors to use in determining when to preempt and then to migrate a process. These include (1) The load average on the current machine (2) The load average on a potential new host (3) The amount of time, CPU overhead, and network overhead required to preempt and migrate the process across the network. Since the goal of migration is to minimize the overall time from process creation to completion, all three factors must be taken into account.

It certainly makes little sense to migrate a process from a machine with a load average of 4 to a machine with a load average of 3, especially since a new job could be started on the more lightly loaded machine while the preempted process is migrating. Also, the load average on the current machine could fall by the time the preempted process migrates since another process could complete in the meantime. Ultimately, there must be a significant difference in load average between the two machines in order for migration to produce better results.

3.4.4 Testing

Testing is a very difficult task and there are many issues associated with it. First of all, there are many variables to take into account when testing. Not all combination of variables can realistically be tested. Hence, a subset of important variable combinations must be used to demonstrate the main aspects of each system. Since a fair amount of randomness exists in each algorithm, many test runs need to be performed to get statistically meaningful data.

Chapter 4

Implementation

The three algorithms were implemented using kali-scheme, a distributed implementation of scheme48 [CJK95]. Using kali-scheme processors can be simulated using threads in a single UNIX process, several UNIX processes on the same physical machine, or several UNIX processes on multiple physical machines.

4.1 Environment

For testing purposes and comparison reasons, three testing environments for all three algorithms were developed. The first environment is a complete simulation; the second is a quasi-simulation; and the third is a full implementation.

In the complete simulation, processes and processors are modeled using threads in a single process. The load and memory requirements of each job are specified when the job is created. This allows the user to control the load of jobs introduced into the system for test purposes. The load average of a processor is simply the sum of the loads of all jobs currently running on that processor. The amount of memory used is the sum of the memory requirements of all jobs currently executing on a particular processor, and the amount of the free memory is the total amount of memory minus the amount of memory used.

Processors are modeled as objects in the object-oriented style and they communicate with one another by sending messages. Jobs are modeled as threads. Whenever a new job is allocated to a processor A , the load and memory of processor A are adjusted and the thread runs. When the job finishes, the load and memory are adjusted again.

Processes in the simulated environment do nothing but sleep for a period time specified by the user. Therefore, simulated processes contributed no actual load to the system.

In the quasi-simulation, processes and processors are still modeled as threads, but each processor object actually resides on a different physical machine. Hence system state information is actually communicated across the network and jobs actually run on different physical machines. Load averages and memory requirements are not given by the user when jobs are created but rather they are calculated by the system. A thread load calculation was implemented for kali-scheme, which is based upon how the Linux operating system computes load averages of processes.

Processes in the quasi-simulation are scheme threads that perform some kind of computation or input/output. They, therefore, contribute load to the scheme process.

Finally, for the full implementation, jobs are not modeled as threads but are real UNIX processes, forked and executed by the system. Real load averages from the OS are obtained for state information. While processors are still modeled using threads within the kali-scheme processes, this is simply for communication and information tracking purposes. Each processor thread in kali-scheme runs on a distinct physical processor since each processor thread resides on a different physical machine. This implementation uses real processors, real processes, real load averages, real memory requirements, real network communication, and real faults. Preemption was not implemented for this approach in order to reduce complexity.

4.2 System Architecture

The design of this system is separated into several entities: processors, processes, communications, logging and statistics generation, each of which can be divided into its constituent parts.

Processors:

- Processor scheduler
- Load average calculator thread

Processes:

- Simulated processes with varying load contributions and execution times
- Scheme threads for the quasi-simulation that perform actual computations
- Real UNIX processes that perform computation

Communications:

- Network daemons
- Messages: token, process creation, etc.
- Ring-procedures (for token-based algorithm)
- Token-procedures (for token-based algorithm)

Logging:

- Processor logging thread
- Scheme-readable format
- Human-readable format

Statistics generation:

- x-y plots of processor load average over time

- x-y plot of average processor load over time
- x-y plot of standard deviation of processor loads over time
- x-y plot of maximum unfairness of processor loads over time
- Process response and execution times
- Hop counts processor request messages
- Counts of message types produced by the system

4.3 Load Average Computation

Load average in the quasi-simulation and in the real implementation is implemented in the following way: Load average is calculated over the past 1, 5, and 15 minutes using an exponential decay algorithm. This gives a weighted average of the current load with previous loads (of 1, 5, and 15 minutes). The current load is defined to be the length of the ready queue. The weight of the current load in calculating the load average over the past minute is $1 - e^{interval-60}$, whereas the weight of the previous load is $e^{interval-60}$, where *interval* is the frequency (in seconds) at which the load is updated. This algorithm was adapted from the Linux kernel implementation coded by Linus Torvalds and appears in figure 4.3.

4.4 Fault tolerance

Processors can be dynamically added and removed from the system. When a processor is added to the system, it broadcasts its state. In the centralized algorithm, it sends a message only to the server. In the same way, when a machine properly shuts down, it sends a message to the server or it broadcasts it to the system. For the distributed algorithms, processor addition and removal requires $O(n)$ messages whereas the centralized algorithm requires only $O(1)$ messages, where n is the number of machines in the system.

Figure 4.1: Load Average Algorithm: Calculates the load average every 5 seconds for the past 1, 5, and 15 minutes.

```
(define calc-load

;; load is a vector of three elements, containing the load average over
;; the last 1, 5, and 15 minutes respectively.
;; ready-Q is the ready-Q of the scheduler.

(lambda (load ready-Q)
  (let*
    ((interval 5000) ; 5 sec
     (exp-1 (exp (* -1 (/ (/ interval 1000) 60))))
     (exp-5 (exp (* -1 (/ (/ interval 1000) 300))))
     (exp-15 (exp (* -1 (/ (/ interval 1000) 900)))))
    (letrec
      ((calculate
        (lambda (which exp-n num-tasks)
          (vector-set! load which
            (+ (* (vector-ref load which) exp-n)
              (* num-tasks (- 1 exp-n))))))
       (update-load
        (lambda ()
          (let
            ((num-tasks (queue-length ready-Q)))
            (calculate 0 exp-1 num-tasks)
            (calculate 1 exp-5 num-tasks)
            (calculate 2 exp-15 num-tasks)
            (sleep interval) ; recalc load every interval
            (update-load))))
        (update-load))))))
```

The token-based algorithm uses the fault tolerance procedures of a generic token algorithm, such as coordinator election in the presence of coordinator failure, token generation whenever a token is lost, and token removal whenever multiple tokens are present.

Whenever a process is created, the machine on which it is created must ensure that the process begins execution on some remote machine. This is accomplished via a reply to the originating machine whenever the process is accepted. The originating machine simply uses a timeout to ensure it receives this response. If not, it broadcasts to all processors it knows about. If it does not receive a reply from a particular processor within a fixed amount of time, that processor is removed from its usage table. The originating machine can also resend the remote-execution request. This ensures at least once execution semantics. This approach provides fault tolerance for process execution and for processor failures.

Instead of timing out on every message, timeouts need only occur to ensure processes are accepted. This considerably reduces the amount of state information and the amount of messages generated in order to incorporate fault tolerance into the algorithms. Essentially, the only message increase occurs when an accept message is not received before the timeout. Then $O(n)$ messages are produced, where n is the the number of processors in the system. However, this occurs very infrequently – only when a processor is assumed to have failed. Otherwise, the system experiences no increase in messages. In the centralized algorithm, only $O(1)$ messages are produced when a timeout occurs.

4.5 Messaging

Messaging is currently provided by a centralized mail server, but can easily be made distributed without effecting the rest of the system, since the mail system is modular.

For group messaging, FIFO broadcast semantics is provided by the mail system. **(Definition) FIFO Broadcast:** All messages sent by a single process will be received in that same order by all recipients. In other words, if processor A sends messages 1 and 2 to processors B and C , then both B and C will receive the messages from A in the same order

they were sent. This scheme allows B to receive both messages 1 and 2 before C receives any messages.

In the simulated token-based algorithm, the token is sent between processors in the logical ring by sending a message to the processor object. In the distributed implementation, since each processor object resides on distinct physical machines, an actual network packet is generated for this token.

Several types of messages exist in the system:

- processor-add: A new processor is available for remote computation.
- processor-remove: A processor is no longer available for remote computation.
- processor-shutdown: Makes a processor shutdown.
- process-create: A process creation request
- process-accept: Message notifying owner of a process that it has been accepted.
- process-done: Message notifying owner of a process that it has completed computation.
- request: Message requesting a machine to accept a process. In the distributed Q-learning algorithm, this message has load information piggybacked onto it.
- alive?: Message asking a remote machine to respond. Used for fault tolerance to ensure a remote processor is still available in case a process request has timed out.
- alive!: Message responding to an alive? message. Indicates that a machine is still available for remote computation.
- token: Used only in the token-based algorithm, this type of message transmits the usage table around the logical ring.
- update: Used only in the distributed Q-learning algorithm, this message is sent to the owning machine when a process has been running remotely for 5 seconds. This allows the load to be affected by the new process.

- log: Used for information gathering, this type of message requests that a processor log its current load information to a log file.

4.6 Processes

Three types of jobs were used to test the system:

- CPU-intensive
 - Simulation: scheme thread sleeps for 35 seconds and contributes a load of 1 to the system load.
 - Quasi-simulation: interpreted scheme thread repeats math multiplication 5,000,000 times.
 - Full implementation: UNIX process written in C repeats math multiplication 150,000,000 times.
- Disk intensive
 - Simulation: scheme thread sleeps for 18 seconds and contributes a load of 0.6 to the system.
 - Quasi-simulation: interpreted scheme thread writes 250,000 characters to to file.
 - Full implementation: UNIX process written in C writes 3,000,000 characters to a file.
- Highly interactive: Job that sleeps, accesses memory, and loops n times. The process is designed this way instead of having user interaction so that the issues of console redirection over the network are avoided.
 - Simulation: scheme thread sleeps for 10 seconds and contributes a load of 0.01 to the system.
 - Quasi-simulation: interpreted scheme thread sleeps for 3 seconds, performs 100 memory operations and loops 6 times.

- Full implementation: UNIX process written in C sleeps for 3 seconds, performs a memory operation and loops 6 times.

4.7 Randomness

For the source of randomness in the distributed Q-learning algorithm, a random number generator distributed with kali-scheme was used.

4.8 Process Migration

Each process maintains a migration count in its process control block. The migration count of a process gets incremented by 1 each time a process migrates to a new machine.

The selection algorithm used is simple. The first process in the process table with the lowest migration count gets selected for migration. The process migration algorithm runs every n seconds. If the load is over a certain threshold and there is a more lightly loaded machine in the (by a certain threshold), then a process is migrated, and its migration count is incremented.

This approach prevents indefinite postponement of processes by ensuring that a process migrated once is not migrated again until every other process on that machine migrates at least once.

4.9 User controlled variables

The following variables are controllable by the user:

- environment: full implementation, quasi-simulation, or simulation.
- process-migration-load-threshold: If a processor's load is greater this threshold, the migrator thread will migrate a process to a more lightly loaded processor
- process-migration-load-diff-threshold: In order for a processor to migrate a process the difference between its load and the minimum loaded processor must be at least this

- process-migration-interval: How often the process migration procedure runs.
- timeout-wait-period: Amount of time a processor waits to receive an ACCEPT message for an offloaded process before invoking fault tolerance procedures
- processor-timeout: Amount of time a processor waits to receive an ALIVE reply from another processor before invoking fault tolerance procedures
- migrate-processes: Should process migration occur?
- token-threshold: How often should the coordinator check to see if it has seen the token?
- coordinator-threshold: How often should machines in the system check to see if the coordinator is alive?
- parameter-p: Used only the distributed Q-learning algorithm, this value is the percentage of time that a processor is chosen at random for offloading a process.
- usage-table-update-interval: Used only in the centralized algorithm, this value is the how often the usage table values are adjusted on the server.

4.10 Logging and Statistics

For statistical purposes, each processor logs its load every n seconds. This log is centralized such that all processors log to the same file. A lock on the file prevents multiple processors from writing to the log simultaneously. In the distributed implementations, a processor calls this logging function as a remote procedure and hence all logging takes place on a single machine. Since the logging function runs on only one machine, a single clock time stamps all log messages. Therefore, clock synchronization is not required in order to correctly interpret the log data.

The following statistics are tracked as the system runs:

- Load average of processors over time
- Memory usage of processors over time.

- Maximum unfairness ($maxLoad - minLoad$) of processors over time.
- Average processor load over time
- Standard deviation of processor load from the average over time.
- Response time: time elapse from process creation to process execution.
- Total elapsed time: time elapse from process creation to process termination.
- Average number of hop counts for all processor request messages.
- Number of local jobs and number of remote jobs for each processor over time.

When the distributed system is shutdown by the user, the log file is converted to a human-readable format, and `gnuplot` data files are automatically generated. The `gnuplot` data includes the load average of each processor over time, the maximum unfairness among processors over time, and the standard deviation of processor loads from the average of all processor loads over time.

The data files generated for `gnuplot` were converted to x-y graphs and are contained in appendix A. Each chart shows load (y-axis) versus time in milliseconds (x-axis). In the load average graphs, each line represents a different processor in the system, and one of the lines represents the average load of all processors in the system.

The other data generated for comparison purposed include (1) the response time and execution times for every process, (2) hop count data for request messages, and (3) counts for each type of message generated during system execution. Samples of this data is contained appendix A.

4.11 Selection policy

For new processes, the selection policy is simple, all new jobs are offloaded if a lower loaded machine exists. For process migration, the policy is to pick the process with the lowest migration count. The system was designed with CPU-intensive jobs in mind, so using the process with the

least migration count avoids choosing the same job time and again to be migrated. Otherwise, a job could be indefinitely postponed.

4.12 Transfer policy

The transfer policy is invoked every time a job is created. The transfer policy also runs every n seconds to check for preemptive migration. For preemptive process migration, the system checks to see if its load is above some threshold. If so, and another machine has a lighter load (within some threshold), then selection and transfer algorithms are invoked. The thresholds and n are all user adjustable.

4.13 Location policy

Figure 4.13 shows an algorithm useful for processor selection (location policy). The actual algorithm used is a scaled-down version that incorporates only load average as a factor. So it is most useful for cpu-intensive jobs.

This location policy algorithm is designed for CPU-intensive processes.

4.14 Placement and Migration Thresholds

The placement and migration thresholds are both static and user adjustable. The placement threshold used for testing purposes was 0.0. The migration threshold was 4.0 and the load difference threshold was 3.0. Therefore, in order to migrate a process, a processor must have a load average of at least 4.0 and there must be at least a difference of at least 3.0 between it and the lowest loaded processor. All new jobs can potentially be offloaded.

The reason a load difference of 3 was used is because any less of a load difference does not justify the overhead involved in transferring the process and its state information to a remote machine. Also, the migration of an already running job must significantly improve its chances of gaining processor time.

```

PROCEDURE calculate_priority BODY
  FOREACH processor in processor_list DO
    processor.priority <- ld_avg_wt * processor.load_avg +
                        mem_wt * processor.free_memory +
                        speed_wt * processor.speed
  OD
ENDPROC

FUNCT find_best_processor returns processor BODY
  IF (local_load < threshold)
  THEN
    return (LOCAL_PROCESSOR)
  ELSE
    filter (processor_list, processor_architecture_for_this_process)
    filter (processor_list, memory_requirements_for_process)
    calculate_priority (processor_list)
    best_processor <- minimum (processor_list, priority)

    return (best_processor)
  FI
ENDFUNCT

```

Figure 4.2: Processor selection algorithm

These placement and migration thresholds are arbitrary and more testing and analysis needs to be performed for better thresholds. Migration was not implemented for the Centralized algorithm since individual machines have no global knowledge, and therefore cannot compare their own load against another load.

Chapter 5

Testing and Results

Since the implementation of the processor allocation algorithms is very flexible, there are many user-controlled variables. Because of these variables and because randomness exists in the systems, test cases need to be designed in order to compare the performance of the algorithms. In order to further compensate for the randomness factor, several runs of each test case are necessary.

5.1 System Variables

The following values can be changed while testing any of the processor allocation algorithms.

- **Number of processors in system.** This can be one or more processors. In the simulation the upper bound is limited by the number of threads that kali-scheme can handle, which depends mostly on the amount of memory available. Through experimentation, kali-scheme can handle thousands of threads simultaneously on a Sparc 5 box with 32 MB of RAM. In the quasi-simulation, one is limited by the number of kali-scheme processes one can run simultaneously. In the full implementation, the user is limited only by the number of machines at his or her availability.

- **Number of processes introduced into system.** In all three environments, the number of processes is limited only by the number of threads that kali-scheme can handle simultaneously.
- **Time distribution of processes.** The time distribution of processes can be fixed or variable. For instance, one could write a script to introduce a single process every n milliseconds, where n is a positive integer. One could also make the interval between process creation completely random.
- **Location distribution of processes.** Processes can be introduced to the system at any processor. Hence one could create all processes on a single machine or one could create processes randomly on all hosts or on a subgroup of hosts.
- **Type of process.** The type of processes created can be one of the following or a mix of all them.
 - CPU-intensive
 - I/O-intensive (disk)
 - Highly interactive
- **Load, memory requirements, and length of processes.** These variables are available only in the simulation environment. In the other environments, load and memory requirements are calculated by the system. Length of a process varies and depends both on the type of process and the load of the processor on which it is running.
- **Speed of processors.** The processors' speed can be homogeneous or heterogeneous.
- **Memory available to processes.** Again, amount of memory available to processes can be homogeneous or heterogeneous.
- **Fault Tolerance.** Are faults, such as network or processor failures, introduced into the system?

- **Testing Environment**

- simulation
- quasi-simulation
- real implementation

- **Preemptive or non-preemptive load balancing.** This option is available only in the simulation and quasi-simulation environments. The full implementation uses only non-preemptive load balancing.
- **User adjustable variables.** These are listed in section 4.9.

5.2 Test Cases

Test cases are divided into several categories to address different issues, such as the effects of testing environment, process type, and process creation interval on the performance of each algorithm. Because process run times vary depending upon the type of process and the load of the processor on which it is running, test runs take a variable amount of time.

1. **Environment, Algorithm, and Process Type.** There are 3 types of environments: Simulation, Quasi-simulation, and full implementation. There are 3 algorithms: Q-learning, Centralized Up-Down, and the token-based algorithm. There are 3 types of processes (cpu-intensive, interactive, and disk-intensive), and mix of all three. The combination of these three variables yields 36 (4 process types * 3 algorithms * 3 environments) test cases.

- (a) Characteristics common to all test cases

- i. Variable creation interval between 0.5 seconds and 10 seconds.
- ii. Each process is created on a random machine
- iii. 5 processors

- iv. Non-preemptive

- (b) Characteristics differing among test cases

- i. CPU intensive processes

- A. 30 processes

- B. Only CPU intensive processes

- C. For simulation, a process with load 1 that runs 35 seconds is used

- ii. Highly interactive processes

- A. 30 processes

- B. Only highly interactive processes

- C. For simulation, a process with load 0.01 that runs 10 seconds is used

- iii. Disk intensive processes

- A. 30 processes

- B. Only disk intensive processes

- C. For simulation, a process with load 0.6 that runs 18 seconds is used

- iv. Mix of process types

- A. 50 processes

- B. A mix of all 3 process types

- C. For simulation, processes have a random load of between 0.01 and 1.0 and run for a random duration of between 1 and 35 seconds

2. **Process Creation Interval.** This test case shows the effects of the process creation interval on the performance of all three algorithms in the quasi-simulation environment. In this test case, a fixed creation interval of 15 seconds exists between each process creation. The results of this test case can be compared against results of the previous test case, where there was a random interval between process creations. This test needs to be run for all three algorithms, hence this generates three more test cases.

- (a) 15 seconds between every process creation
- (b) 30 processes total
- (c) A mix of all 3 process types
- (d) Each process is created on a random machine
- (e) Quasi-simulation environment
- (f) 5 processors
- (g) Non-preemptive

3. **Scalability.** This test case is performed only in quasi-simulation environment since there are a limited number of physical machines available for testing. Three different system sizes (1, 5, 14) are used to collect data for all three algorithms. Hence, there are 9 test cases for scalability.

- (a) Number of processors (1, 5, 14)
- (b) Quasi-simulation environment
- (c) Non-preemptive
- (d) 50 processes total
- (e) Processes created on random machines
- (f) Mix of all 3 process types
- (g) Random amount of time between 0.5 seconds and 15 seconds between each process creation request

4. **Location of process introduction.** This test case shows the effects of where a process is created has on the system. Since we already have data for process creations at random hosts, we need only gather data for all process creations at a single host. Since we need to test this for all three algorithms, this generates 3 test cases.

- (a) 30 processes total

- (b) Quasi-simulation environment
- (c) All processes are created on the same machine
- (d) 15 seconds between each process creation
- (e) A mix of all 3 process types

5. **Fault Tolerance.** There are four items to test for all three algorithms; hence, this generates 12 test cases.

- (a) Processor failures
- (b) Processor additions during runtime
- (c) Network failures
- (d) Network delays

Total Test Cases = 50

Three iterations of each test case * 50 test cases = 150

5.3 Results

5.3.1 Process Creation Request Hop Counts

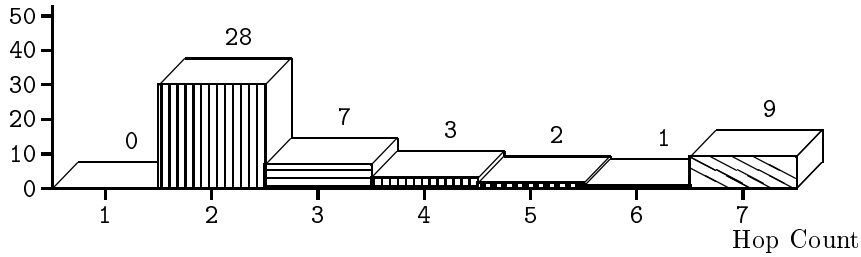
The following bar chart shows how many requests messages took which number of hops before being accepted by a processor. Hop count is defined as follows: A request message starts with a hop count of 1. Each time the message gets passed to a machine, its hop count gets incremented. When a process request message is accepted, the message gets destroyed and hence the final hop count is the value of the hop count when the message gets accepted.

The hop count of request messages is important to measure because as hop count increases so does response time. Hence, we would like to reduce the hop count of request messages as much as possible. Hop count is one factor in measuring the network overhead of an algorithm.

Hypothesis: For the centralized and token-based algorithms, the hop count for request messages should be constant for all processes. For the distributed Q-learning algorithm,

processes will require a variable number of hops before being accepted. Most of the hop counts should be low, though (2 or 3 hops).

No.



Q-learning algorithm in quasi-simulation environment. 5 processors, 50 processes of mixed process types. Average of 3 test runs.

Figure 5.1: Hop Counts for Q-learning Algorithm

Results: In the Q-learning algorithm, a process creation request can travel to several machines before it is accepted somewhere. In order to prevent indefinite postponement, there is an upper limit on the hop count. This limit is the size of system plus 2. This limit allows a creation request to potentially visit every machine in the system plus one machine twice (process creation counts as one hop).

In this case, the system size is 5, so the hop count is limited to 7. This hop count limit is arbitrary; however, if the request bounces more times than the number of machines in the system, then bad decisions are apparently being made, and the request simply needs to be accepted by some machine.

More than half of process creation requests are accepted at the first machine at which they arrive. This is a good indication that the algorithm is learning well.

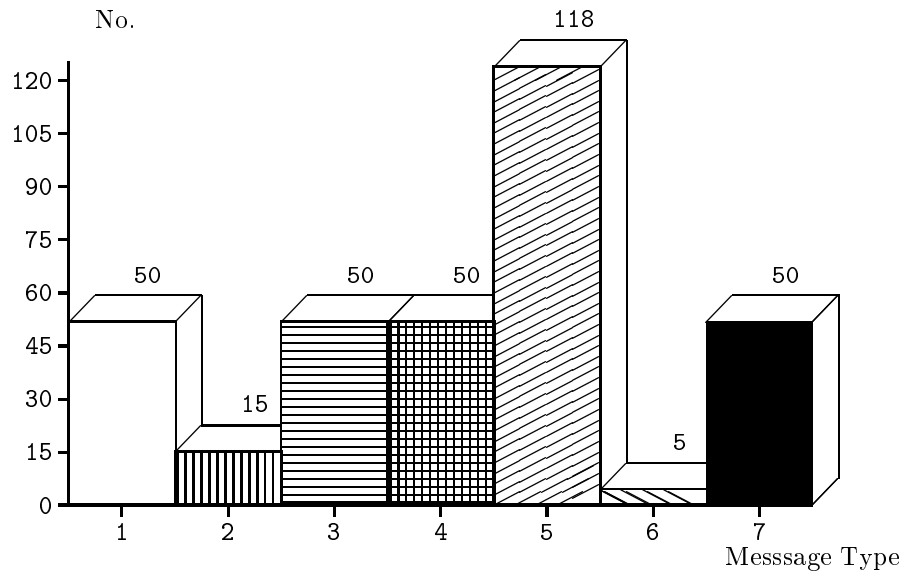
The hop count for all process creation requests is 3 in the centralized algorithm. The first hop is the creation of the process at any host in the system. The second hop is when the creation request is sent to the server. The third and final hop is the spawning of the job on the remote machine as determined by the server.

In the token-based algorithm, all process creation requests take exactly two hops. The first hop is the creation of the process on a node. The second hop is the offloading of the process.

5.3.2 Number of Messages Generated per Algorithm

The number of messages generated by an algorithm shows its network overhead. Whereas the previous bar chart showed only hop counts for request messages, the following bar charts shows counts for each type of message. Whereas some of these numbers remain constant among the three different algorithms, they differ for others, such as process-creation message and processor-create messages.

Hypothesis: Process-accept, and process-done messages should remain constant for all three algorithms, one message for each process. Process request messages will be variable for the distributed Q-learning algorithm. Process-create messages should be twice the number of processes for the centralized algorithm, but equal to the number of processes for the distributed algorithms. Processor-add and processor-done messages should be higher for the distributed algorithms than for the centralized algorithm since more processors need to be sent such messages.



Legend

- 1 – process-accept
- 2 – processor-add
- 3 – process-create
- 4 – process-done
- 5 – process-request
- 6 – processor-shutdown
- 7 – update

Q-learning algorithm in the quasi-simulation environment. 50 processes, 5 processes, and a mix of process types. Average of 3 iterations.

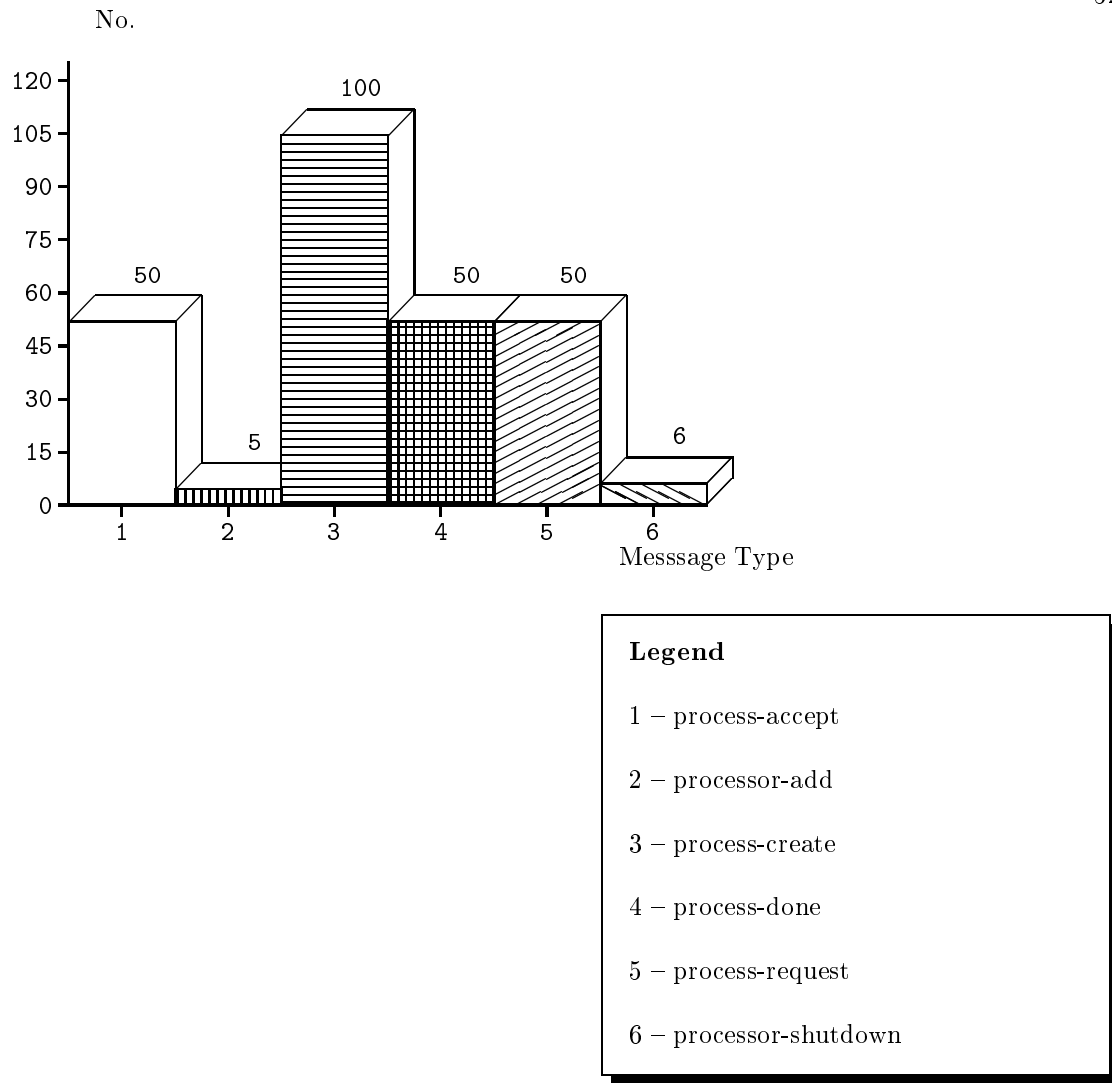
Figure 5.2: Messages Generated for Q-learning Algorithm

The distributed Q-learning algorithm produces a single creation message for each process. The number of request messages is variable since a processor may forward a request message or it may accept it. There is a single process-accept and a single process-done message for each process.

There are 15 processor-add messages for a system with 5 processors. This is because the first processor sends a message only to itself. The second processor sends a processor add message to itself and to the first processor, etc. Hence in a system with 5 processors, $1 + 2 + 3 + 4 + 5 = 15$ processor addition messages. In a system with n processors, there will be $1 + 2 + \dots + n$ processor addition messages.

For processor shutdowns, there are only 5 messages. This is because instead of broadcasting a shutdown, the processor notifies only the mail server. Whenever a processor tries to communicate with a processor that has already shutdown, the mail server lets the requester know that the requestee has shutdown. The requestee is then free to communicate with another machine.

There are 50 processor update messages. For each process, an update message is sent from the accepting machine to the machine where the process was created 5 seconds after the process starts running.

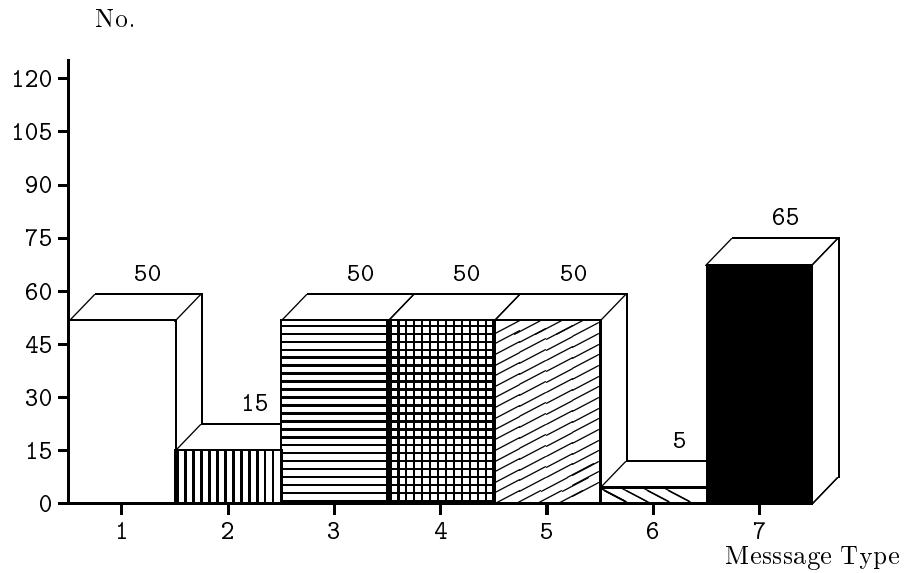


Centralized algorithm in the quasi-simulation environment. 50 processes, 5 processes, and a mix of process types. Average of 3 iterations

Figure 5.3: Messages Generated for Centralized Algorithm

The centralized algorithm produces a single request message for each process. However, it produces 2 create messages for each process. The first create message occurs on a client machine. The second create message occurs on the server when the creation request is forwarded there. There is a single process-done and a single process-accept message for each process. There is a

single processor-add message for each processor and a single process-shutdown message for each processor (including one for the server).



Legend

- 1 – process-accept
- 2 – processor-add
- 3 – process-create
- 4 – process-done
- 5 – process-request
- 6 – processor-shutdown
- 7 – token

Token-based algorithm in the quasi-simulation environment. 50 processes, 5 processes, and a mix of process types. Average of 3 iterations.

Figure 5.4: Messages Generated for Token-based Algorithm

Results: There is a single create, request, accept, and done message for every process. As in the distributed Q-learning algorithm, there are $1 + 2 + \dots + n$ processor-add messages and n processor-shutdown messages for a system with n processors.

Additionally, the token-based algorithm generates token messages. A token message is defined to be the transfer of the token between two machines. Hence, in this test case, there was an average of 65 token transmissions.

5.3.3 Process Creation Interval

Average load average over time is the average value of all load averages for all processors over time. Whereas, in the chart below, the average load average is the average value of the average load average over time for 3 test runs.

In other words, load is a function of processor p and time (indicated by $t = 1, 2, \dots, t_{max}$) at which it is measured. Therefore, let load be denoted by $l(p, t)$. Then, $l(p)$ is the average load for processor p over time. Let $L(t)$ be the average of $l(p, t) \forall p$. Therefore L (otherwise referred to as average load) is average of $L(t) \forall t$. Finally, since there are 3 runs of each test case, we need to average the average load L over all test runs, where a particular test run is denoted by i . Hence, let LL be the average of $L_i \forall i$.

Similar equations hold true for maximum unfairness among processor loads and for standard deviation of processor loads from the mean. Let $U(t)$ be the maximum unfairness over time t . Again, maximum unfairness is defined to be the difference between the most highly loaded and most lightly loaded processors in the system at time t . Then, U is the average of $U(t) \forall t$. Finally, let UU be the average of $U_i \forall i$, where i denotes a test run.

Let $S(t)$ be the standard deviation from the average load at time t . Then, S is the average of $S(t) \forall t$. D_i is the standard deviation of S for test run i , and D is the average of $D_i \forall i$. Finally, let SS , otherwise referred to as the average standard deviation be the average of $S_i \forall i$.

Random Creation Interval between 0.5 and 10 seconds.

	Q-learning	Centralized	Token
Avg. Load	1.361 (0.840, 1,188)	1.968 (0.671, 1.064)	2.380 (1.488, 2.422)
Avg. Maximum Unfairness	2.513 (3.613)	2.104 (3.294)	4.578 (7.890)

Fixed Creation Interval of 15 seconds

	Q-learning	Centralized	Token
Avg. Load	0.375 (0.210, 0.345)	0.838 (0.388, 0.699)	1.276 (0.542, 0.701)
Avg. Maximum Unfairness	0.648 (1.053)	1.283 (2.364)	1.705 (2.273)

Quasi-simulation environment, 5 processors, 30 processes with a random mix of all process types. Average standard deviation (SS) from the load followed by standard deviation (D) from the average standard deviation are in parenthesis.

Figure 5.5: Comparison of Process Creation Interval

Processor load averages are lower for the fixed creation interval testing. Since a greater time elapse occurs between creation requests, this gives currently running processes more time to contend for the cpu with fewer processes. Also, the algorithms tend to have more time to propagate data showing the effects of currently running processes. Hence, better decisions are being made as to where to offload processes.

The large standard deviations for maximum unfairness are explained by a large difference in load for a single processor near the end of execution. This is explained in detail in section 5.4.3.

5.3.4 Location of Process Creation

Creation of processes on random hosts

	Q-learning	Centralized	Token
Avg. Load	1.361 (0.840, 1,188)	1.968 (0.671, 1.064)	2.380 (1.488, 2.422)
Avg. Maximum Unfairness	2.513 (3.613)	2.104 (3.294)	4.578 (7.890)

Creation of processes on a single host

	Q-learning	Centralized	Token
Avg. Load	0.308 (0.188, 0.292)	0.956 (0.257, 0.373)	1.492 (0.721, 1.257)
Avg. Maximum Unfairness	0.599 (0.937)	0.929 (1.299)	2.367 (4.113)

Quasi-simulation environment, 5 processors, 30 processes with a random mix of all process types. Average standard deviation (SS) from the load followed by standard deviation (D) from the average standard deviation are in parenthesis.

Figure 5.6: Comparison of Process Creation Location

Hypothesis: One would expect different, perhaps better, results from the distributed Q-learning algorithm and the token-based algorithm. For the centralized algorithm, theoretically, there should be no difference in performance.

Results: For the Q-learning algorithm, since only one usage table is used for decision making, this will propagate the effects of the decisions based on the accuracy of the one usage table. Since one machine handles all process creation requests, one would expect it to gain better information about the system than if it received only a fraction of the requests. This is because the single machine communicates more and gets more up-to-date information. In fact, this does occur according to the results presented in the previous table.

For the token based algorithm, the single processor enqueues all creation requests until it receives the token. Hence, one would expect the single machine to offload all of its current creation requests to a single machine (the one with the lowest load average) simultaneously. One would also expect this to skew the load averages and to create a large standard deviation and a large maximum unfairness value. This does not occur or did not, at least, in these test results. This can be explained by the randomness in the algorithms induced by variable creation interval and variable process type.

If the token circulates quickly enough between creation requests, then the single machine offloading processes has more up to date information than the machine directly following the one offloading the requests. Assume processor n and $n + 1$ offload all processes. After process n has offloaded its processes, perhaps to processor m , then processor $n + 1$ receives the token. The token has stale load average information about processor m , and hence processor $n + 1$ will offload its creation requests to processor m as well. It is not until the token reaches processor m , that the token has more up-to-date information. Thus, this explains why the load averages might turn out lower when all creation requests occur on a single host.

The only explanation for the lower load averages in the centralized algorithm for the single host for creation requests is randomness in creation interval and in process type.

5.3.5 Scalability

The following table shows average total process time, average process run time, and average process response time. Response time is the time elapse from process creation to process execution. Run time is the time from process execution to process completion. Total process time is the time from process creation to process completion. Hence total process time = response time + run time.

Let $t(p)$ be a function mapping a sequential process id to a total process time. Let $r(p)$ be a function mapping process id's to response times. Finally, let $run(p)$ be a function mapping process id's to run times.

$$t_{avg} = \frac{\sum_{p=1}^{p_{max}} t(p)}{p_{max}}$$

$$r_{avg} = \frac{\sum_{p=1}^{p_{max}} r(p)}{p_{max}}$$

$$run_{avg} = \frac{\sum_{p=1}^{p_{max}} run(p)}{p_{max}}$$

Hence, $t_{avg} = r_{avg} + run_{avg}$

No. Processors	Q-learning	Centralized	Token
1	509.246 = 342.024 + 167.222	584.473 = 252.833 + 331.639	526.507 = 295.887 + 230.621
5	95.4852 = 34.187 + 61.299	116.542 = 15.637 + 100.905	165.108 = 53.834 + 111.274
14	78.512 = 26.491 + 52.026	82.825 = 18.174 + 64.651	202.051 = 43.784 + 158.267

* Average of 3 iterations. Quasi-simulation. 30 CPU-intensive processes. Random creation interval between 0.5 and 10 seconds.

Figure 5.7: Algorithm scalability

Average Load (Average Standard Deviation, Standard Deviation)

Environment	Q-learning	Centralized	Token
1	4.445 (0.0, 0.0)	9.269 (0.0, 0.0)	6.449 (0.0, 0.0)
5	0.853 (0.427, 0.730)	1.644 (0.796, 1.398)	2.180 (1.851, 2,949)
14	0.350 (0.252, 0.122)	0.982 (0.324, 0.154)	1.039 (0.805, 0.441)

Average Maximum Unfairness (Standard Deviation)

Environment	Q-learning	Centralized	Token
1	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
5	1.397 (2.398)	2.609 (4.447)	5.914 (9.141)
14	1.246 (0.740)	1.709 (0.679)	4.488 (2.380)

* Average of 3 iterations. Quasi-simulation. 30 cpu-intensive processes. Random creation interval between 0.5 and 10 seconds

Figure 5.8: Algorithm scalability. Data shown for test A

Hypothesis: As the number of processors increase, the average load and the average run times should decrease for all three algorithms.

Results: In general, as the number of processors increase, the average run time and system time decrease. The only exception is the token algorithm, whose run time and execution time increase from 5 processors to 14 processors.

This inconsistency is explained by the delay in information propagation due to the time the token takes to circulate to all machines. As the number of processors increases, so does the amount of time taken by the token to circulate the ring. Hence, data becomes more stale. Alterations to the token algorithm could improve its performance inadequacy due to scale (see section 6.5).

5.3.6 Environment

The following tables show results from changing the test environment for all process types.

Hypothesis: The average loads, standard deviations, and maximum unfairnesses should not be affected by the testing environment. For each process type, the respective results should be similar; however, results (average load, standard deviation, and maximum unfairness) will vary between process types since each process type contributes a different amount of load to the system.

Average Load (Average Standard Deviation, Standard Deviation)

Environment	Q-learning	Centralized	Token
Simulation	0.926 (0.471, 0.789)	0.913 (0.630, 1.004)	0.924 (0.340, 0.563)
Quasi-simulation	0.853 (0.427, 0.730)	1.644 (0.796, 1.398)	2.180 (1.851, 2,949)
Full implementation	0.842 (0.584, 0.706)	0.562 (0.194, 0.251)	1.045 (0.421, 0.722)

Average Maximum Unfairness (Standard Deviation)

Environment	Q-learning	Centralized	Token
Simulation	1.380 (2.311)	1.842 (2.130)	1.029 (1.679)
Quasi-simulation	1.397 (2.398)	2.609 (4.447)	5.914 (9.141)
Full implementation	1.781 (2.172)	0.590 (0.729)	1.366 (2.201)

* Average of 3 test runs. Quasi-simulation. cpu-intensive process types. 30 processes.

Figure 5.9: Environment stats. Data shown for cpu-intensive processes

Results: In general, the numbers are fairly similar among environments for load average and standard deviation. The biggest difference is for the token-based algorithm in the quasi-simulation environment. It also has a large difference for its maximum unfairness value. This is attributable to the overhead of running both process threads and system threads within a single scheme process. The scheme process has so many threads to manage and since several

of them are cpu intensive, the timeliness of its thread servicing is somewhat lacking. This is especially true for the token-based algorithm because it has the most cpu overhead.

Average Load (Average Standard Deviation, Standard Deviation)

Environment	Q-learning	Centralized	Token
Simulation	0.002 (0.003, 0.004)	0.003 (0.004, 0.006)	0.002 (0.003, 0.005)
Quasi-simulation	0.000 (0.000, 0.000)	0.156 (0.143, 0.239)	0.059 (0.055, 0.083)
Full implementation	0.109 (0.037, 0.059)	0.128 (0.063, 0.118)	0.326 (0.121, 0.206)

Average Maximum Unfairness (Standard Deviation)

Environment	Q-learning	Centralized	Token
Simulation	0.007 (0.011)	0.010 (0.160)	0.007 (0.011)
Quasi-simulation	0.000 (0.0)	0.331 (0.533)	0.163 (0.257)
Full implementation	0.127 (0.208)	0.207 (0.393)	0.376 (0.623)

* Average of 3 iterations. Quasi-simulation. highly interactive process types. 30 processes.

Figure 5.10: Environment stats. Data shown for highly-interactive processes.

Results: For test cases with highly-interactive processes, all three algorithms function much more similarly than for the other process types. The highly-interactive processes contribute very little load to the system since they sleep most of the time. This gives the processor allocation algorithms ample cpu time.

Average Load (Average Standard Deviation, Standard Deviation)

Environment	Q-learning	Centralized	Token
Simulation	0.287 (0.225, 0.375)	0.274 (0.290, 0.506)	0.180 (0.137, 0.148)
Quasi-simulation	2.370 (1.156, 1.813)	3.889 (2.100, 3.333)	2.827 (1.615, 2,635)
Full implementation	0.237 (0.097, 0.184)	0.254 (0.119, 0.203)	0.597 (0.300, 0.340)

Average Maximum Unfairness (Standard Deviation)

Environment	Q-learning	Centralized	Token
Simulation	0.601 (1.014)	0.809 (1.442)	0.328 (0.333)
Quasi-simulation	3.560 (5.322)	6.147 (9.455)	5.217 (8.422)
Full implementation	0.327 (0.621)	0.366 (0.595)	1.017 (1.156)

* Average of 3 iterations. Quasi-simulation. disk-intensive process types. 30 processes.

Figure 5.11: Environment stats. Data shown for disk-intensive processes.

Results: The quasi-simulation results are very much different from the simulation and full implementation results with disk-intensive processes. This can be attributed to the high overhead of disk intensity in scheme. When a single thread in scheme blocks on disk i/o, the whole scheme process blocks on i/o since there is no underlying OS support for the scheme threads. Also, the scheme threads doing the disk output are interpreted. Hence, there is a much higher overhead of doing disk i/o from a scheme thread than from a UNIX process. Even so, the scheme threads wrote only 250,000 bytes to a file, whereas the UNIX processes wrote 3,000,000 characters to a file. Obviously, it is very difficult to compare scheme disk-intensive threads to UNIX disk-intensive processes in terms of load average.

Average Load (Average Standard Deviation, Standard Deviation)

Environment	Q-learning	Centralized	Token
Simulation	0.305 (0.241, 0.389)	0.301 (0.291, 0.506)	0.251 (0.198, 0.333)
Quasi-simulation	1.361 (0.840, 1,188)	1.968 (0.671, 1.064)	2.380 (1.488, 2.422)
Full implementation	0.472 (0.251, 0.333)	0.386 (0.147, 0.254)	0.721 (0.319, 0.512)

Average Maximum Unfairness (Standard Deviation)

Environment	Q-learning	Centralized	Token
Simulation	0.700 (1.148)	0.860 (1.457)	0.600 (0.995)
Quasi-simulation	2.513 (3.613)	2.104 (3.294)	4.578 (7.890)
Full implementation	0.810 (1.038)	0.460 (0.829)	1.030 (1.649)

* Average of 3 iterations. Quasi-simulation. Mix of 3 process types. 50 processes.

Figure 5.12: Environment stats. Data shown for a mix of all process types.

Results: Again, the numbers for the simulation and the full implementation are similar, whereas the quasi-simulation numbers are much higher. This is due to the disk-intensive threads, as explained above.

5.4 Analysis

5.4.1 Environment

The reason for implementing three environments for the processor allocation algorithms was to determine how well the results compared among the environments. Many researchers develop only simulations, if they develop anything at all, to test out their algorithms. It is often important to go a step beyond that and see how an algorithm works in reality. Too often, simulations do not accurately represent real circumstances.

For example, the simulation used to test these three algorithms could not take into account network failures or delays. Whereas network failures and delays could have been simulated, in reality they are very difficult to simulate.

Another naive assumption made when designing this particular simulation was that the amount of load contributed by a process to the system load would instantly appear in the system load for quick relay to other machines.

In reality, system load is not instantaneously adjusted when a process starts. It takes at least a minute for the system load to show the full effects of a process. Whereas the load average over the last minute does get updated every 5 seconds in the full implementation, because it is an average, the exponential decay function takes time to incorporate a process' effect on the system load. If the system load is averaged over the past 5 or 15 minutes, then the process' effect on the system takes even longer to realize.

Another naive assumption made when designing the simulation was that a process takes the same amount of time to run every time it runs. This simply is not the case. On a lightly loaded machine, a process may complete in a relatively short time period. However, on a heavily loaded machine, even with a faster processor, the same process may take several times that amount of time to run. Because there is much contention for the cpu on a heavily loaded machine, that process has to wait much longer in an idle state in between cpu time slices. Because in the simulation, processes are modeled as threads that sleep for an amount of time, they do not take cpu contention into account.

Hence, it becomes apparent that a simulation may not take into account real circumstances. Algorithms can easily be designed around incorrect or poor assumptions and when they are used under real circumstances, their performance may be very different than under simulation conditions.

On the other hand, the quasi-simulation performed much more similar to the full implementation than did the simulation. The quasi-simulation did take into account network failures and delays. It also used threads that performed work to model processes. Most

importantly, it used a system calculated thread load average that incorporated the exponential decay function. Hence, load averages were realistic and incorporated time into their values.

The only differences between the quasi-simulation and the full implementation are (1) the full implementation used real UNIX processes, (2) the load average was obtained from the UNIX operating system, and (3) each processor was a physical cpu whereas in the quasi-simulation, a processor was represent by a scheme process.

For these reasons, the quasi-simulation and full implementation performed much more realistically than did the simulation.

5.4.2 Process Type

Based upon process run times, all three algorithms performed well for cpu-intensive processes, disk-intensive processes, and a mix of all three processes. For highly interactive processes, the algorithms did not improve process completion time. Indeed, completion times even were longer due to increased response times. Since the highly interactive processes used little cpu time, it makes little sense to offload them.

5.4.3 Load Averages near the end of execution

The results from testing all three algorithms often show one processor in the latter part of system execution to have a load average much higher than the other processors in the system. This causes the standard deviation for the maximum unfairness to be very high for most test runs. This inequity occurs for several reasons:

- It takes time for processes to have an effect on the system load.
- No new processes are being created near the end of system execution.
- Since many processes are running on the same machine, there is cpu contention and it takes a long time for these processes to finish running – the reason for using a processor allocation algorithm.

5.4.4 Algorithms

The centralized algorithm is much simpler than the distributed ones and fault tolerance was very easy to incorporate. It by far produces the least number of messages. The biggest disadvantage to the centralized algorithm is that the server is a single point of failure. However, more fault tolerance could be added to the algorithm to make it continue in the face of server failure. This would increase the complexity of the algorithm and the network traffic. Otherwise, the centralized algorithm is quite tolerant to failures. Processes and processors (other than the server) can fail and the system will continue to function.

Based upon average loads, standard deviations, and process completion times, the centralized algorithm works best for cpu-intensive and disk-intensive processes and a collection of homogeneous machines. When processor speeds and disk speeds vary among machines the centralized algorithm does not work as well as the other two algorithms because it does not use real load averages, and the numbers it computes treats all machines alike.

The token-based algorithm has the most overhead. In general, it performs worse than the other two algorithms in terms of load balancing. Modifications could be made to the algorithm to make it perform better.

Based upon average loads, standard deviations, and process completion time, the distributed Q-learning algorithm performs well under most test cases and is the most versatile of the three algorithms. From the charts in section 5.3.6, one can see that the average loads and standard deviations are generally lower (substantially in some cases) than those of the centralized and the token-based algorithms.

In terms of load balancing, all three algorithms performed the best in the full implementation for cpu-intensive processes. See the graphs in appendix A. There was a low standard deviation and a low maximum unfairness value for all iterations of these test cases. This enforces the concept that the algorithms are designed for cpu-intensive jobs (since load average is the factor in determining location policy). This also enforces the idea that perhaps other metrics are needed for the location policy of highly-interactive and disk-intensive jobs. See section 6.7.

Chapter 6

Conclusions

Experimentation shows all three algorithms perform load balancing for varying types of processes. The following discusses how each algorithm performed in test cases according to the criteria set forth in section 3.3.

6.1 Transparency

The main objective of all three algorithms is to perform load balancing transparently. After system startup, all three algorithms provide transparency to the user. A user creates a process. As soon as the process is created, it is potentially offloaded, unknown to the user.

The part of the system that is not transparent to the user is the startup of the system. The user must tell the system which machines to use for potential offloading of processes. This is a logical step, but potentially only has to be performed one time.

Should any of the processor allocation algorithms be incorporated into an operating system, the initial step of specifying which machines to use for remote computation could be performed once by writing a configuration file. The end user could be completely unaware of the remote computation mechanism. Whenever s/he launched a process from a shell, it might be offloaded, completely unknown to the user. The most analogous situation to this is the use of a network

file system. The end user is completely unaware of where files physically reside. Logically, they appear in a the hierarchical tree structure on every machine.

With mechanisms for remote use of resources and console redirection, an operating system could offload any type of process. Otherwise, the system could offload only processes it knew to be non-interactive and not dependent upon local resources. However, console redirection and the use of remote resources is not a difficult problem to solve and several operating systems, such as Plan 9 [PPTT], already support such operations.

6.2 Flexibility

Since the system is modular and because much code is shared among the three algorithms, the system can easily be altered to use different algorithms. This prevents writing an entire system from scratch when a new algorithm comes to mind. Since the system functions in three different environments (simulation, quasi-simulation, and full implementation), it can be used for testing an idea and for using an implementation in practice.

Since the system is designed around a mailbox approach for communication, new types of messages can easily be added to the system without effecting other parts of the system. This mailbox system is so modular that only a few lines of code are altered for the quasi-implementation and the full implementation.

Another flexible part of the system is the object-oriented approach used to design and implement components of the system such as processor representations and messages. Since a message object has get and set functions, any modification to the message object design can take place in a central location. In order to modify any part of a message, a function must call a message set routine (part of the message object). Therefore, if the format of a message changes or if the data is stored in a special format, this remains transparent to the calling function. Any changes can be made in the message object definition and nowhere else.

Because of the modularity, reuse, and object-oriented design of the system, the system is very flexible and can be easily modified to meet needs of the user.

6.3 Reliability

As shown in test cases, all three algorithms continue to function in the presence of processor additions and failures. The only exception to this is when the server fails in the centralized algorithm.

The system also runs when network delays occur. However, process creation and load sharing information are arbitrarily postponed due to network delays although running processes continue to execute.

A single network link failure is viewed as a processor failure, so the system can continue to function when this occurs. Because the system relies so heavily on the network, it does not continue to function in the presence of total network failure, however. The system could be altered to function in the presence of total network failure by having the algorithms create all processes locally whenever network failure occurs.

In the token-based algorithm, the system can continue to function in most cases in spite of a coordinator failure before a new coordinator is elected. If a token is lost when the coordinator fails, then the system must wait until a new coordinator is elected before the system can resume since the token must be present for system functionality.

6.4 Performance

Performance is quantified by the metrics given in section 3.3.2. As noted already, the distributed Q-learning algorithm is the most versatile of the three algorithms and performs the best overall due to its lower average load averages and lower maximum unfairness values.

6.5 Scalability

Scalability tests show that the centralized and distributed Q-learning algorithms both scale well. Average load decreases as the number of processors increase. Also, process run times decrease as scale increases. This is a good sign of scalability.

The centralized algorithm is scalable to the point where the server is no longer effective at handling the number of processors in the system. Whereas, no experimental data exists to determine the point where the server becomes a bottleneck, one can conjecture that it is several hundred machines.

The distributed Q-learning algorithm is as scalable as the centralized algorithm, if not more so. The amount of overhead for each machine is high as the number of processors increase, since a value in the usage table exists for each processor. Also, it is more difficult to collect “good” information about all processors as the number of processors grows. Hence, hop counts of request messages are likely to increase.

The token-based algorithm, in its present form, is the least scalable of the three algorithms. This is shown quantitatively by the data presented in section 5.3.5. As the system size increases from five processors to fourteen processors, the average load does not decrease, as it does for the other two algorithms.

6.6 Future Work

6.6.1 Algorithms

Alterations could be made to the algorithms to help correct the problem of large standard deviations in average load near the end of system execution. These include the following.

- One might not always choose the lowest loaded processor for process placement. Instead, if a single processor has been chosen for process placement the past n times, then perhaps the next loaded processor could be chosen. This could improve performance since time must pass before a process significantly affects the load of a system.
- One could use the load average over the past minute and 5 minutes to determine whether the load is going up or down. If the load average is going up, then another lightly loaded machine whose load average is going down could be chosen.

- Another alternative is simply to leave the algorithms unaltered and to allow preemptive migration to take care of the situation.

Other alterations to the algorithms are also possible. For instance, the token-based algorithm could be modified such that each processor keeps a local copy of the last known token. Whenever a process is created, it can be immediately offloaded, instead of waiting to receive the token. The token could pass twice around the ring every n seconds to update the processor loads. It would need to pass twice because the first machine to receive the token would get stale load averages during the first token circulation. Hence, on the first pass, all machines would write load information to the token, and on the second pass all machines would read information from the token.

Better process migration decisions could be incorporated into the algorithms and test cases could be devised and run to determine better threshold values for migration policies.

6.6.2 Analysis/Testing

More statistics, such as the following, could be gathered and computed to compare processor allocation algorithms.

- CPU overhead of algorithms.
- Determination of migration overhead.

Other future work includes incorporating processor allocation algorithms with user preference files and with static programmer information given at compile time.

6.7 Implications

For selection policy, when choosing a process to migrate, the best choices are CPU-intensive jobs and disk intensive jobs. Interactive jobs usually should reside on the machine where their user is. Interactive jobs (such as shells) spend the majority of their time blocked on user input; hence, they are using very little CPU time and contributing an insignificant amount of load to

the system. By migrating a highly interactive process to a remote machine, performance will degrade because of the network delays introduced. Still, since the network is generally faster than humans can respond (by typing or clicking), it does make sense to offload an interactive process in some situations, especially if the process is a hybrid of interactive and compute intensive.

For location policy, when choosing a location to place a process, it makes sense to choose a machine with the lowest load average when moving a CPU-intensive job. When moving a disk intensive job, it makes more sense to move it to the machine hosting the disk or at least to a machine with high network bandwidth and low latency between it and the machine (file server) hosting the disk.

Hence, there seems to be a relationship between the resources needed and location policy. Disk-intensive processes need to be as close to their resource (the disk) as possible. CPU-intensive processes need to running on a lightly loaded CPU, and interactive processes should be close to their fundamental resource, the user.

The results of this research argue for a distributed system which includes light-weight desktop machines connected to heavy-weight compute servers which are tightly coupled with file servers. All user processes would originate on the desktop machine. Highly interactive processes would remain on the desktop machine, whereas compute-intensive processes could be automatically migrated to compute servers, unbeknownst to the user. An alternative to starting all user processes locally is for the system to keep track of which programs should be offloaded when they are executed. This could be maintained automatically by the system based upon past performance and/or specified by the user via a configuration file or by the programmer during development. The extreme extrapolation of this idea is a “Network Computer” on every user’s desktop with compute servers and file servers. This would be the most efficient use of resources.

Another implication for process migration is in software development. The relationship between resources needed by a process and a processes location policy entails something more complex. Processes often use many resources intensively, often at different points of execution.

A process may spend most of its time blocked on user input. However, when input is received the process may spend much of its time in the CPU before it checks again for user input. This can overload a machine and be a cause for process migration. However, since the process is mostly interactive, we do not want to migrate the whole process. Instead, we wish to migrate only the part that is CPU intensive. Hence, programmers should code their programs using threads and even specify the thread's main resource (CPU, disk, user). I/O intensive threads can reside on the user's desktop whereas CPU and disk-intensive threads can be migrated, each coming as close as possible to their most needed resource.

It may seem that asking the program to build multi-threaded programs in this way is burdensome; however, this is a natural and logical method for building programs and many programs are written in this way already. For example, the UNIX program `talk` has a process that reads and a process that writes. [Fuc95] argues for such an approach. Recently, programming with concurrency has become less the propriety domain of the operating system developer and more the domain of the application's developer. Evidence that applications are written with concurrency abounds. Witness the multi-threaded capabilities of Java and scheme as well as the growing popularity of UNIX threads, such as Solaris threads and p-threads.

Additionally, many client/server applications are now becoming even more partitioned in that n-tier applications are being developed. For example, a thin client attaches to a compute server, which is attached to multiple database servers. Commercial support for concurrency (for example, Java threads and Oracle database servers) has made possible many distributed applications. However, the distributed nature of these applications is determined in large part at compile time by the programmer. The evolution of this progression is that the distributed nature of application would be determined dynamically at execution. Processor (or Resource) allocation algorithms give this ability to dynamically choose the best processor for a given process or its threads rather than have this information static.

Appendix A

Test Cases

The following charts show load averages over time, maximum unfairness over time, and standard deviation from average load over time. Due to the massive amount of information collected, charts are shown only for a sampling of test cases run. For the graphs plotting load, each line represents a different processor, except one of the lines which represents the average load of all processors.

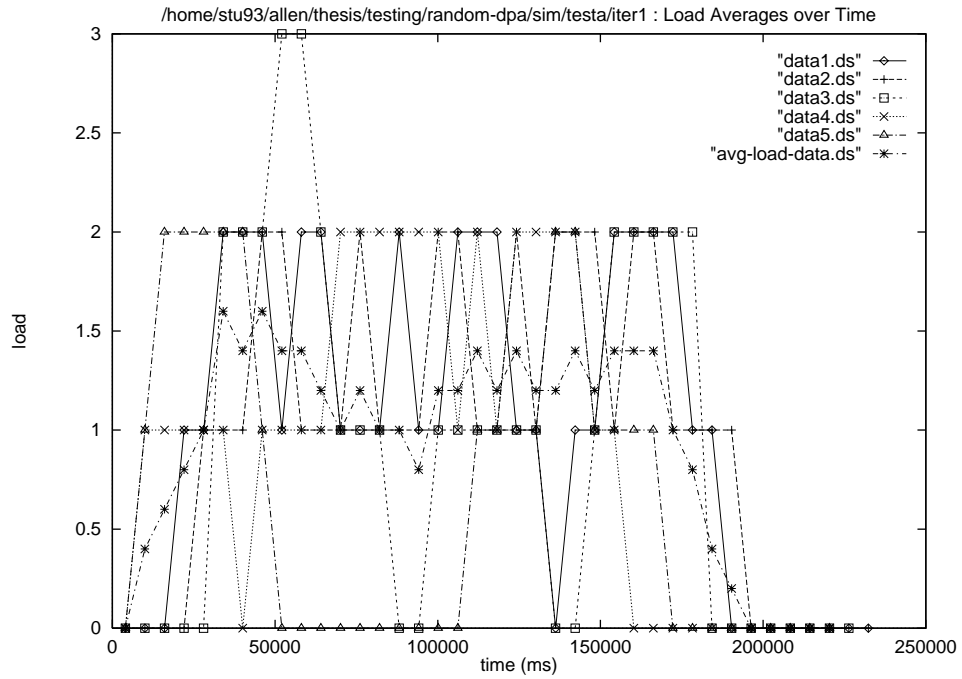


Figure A.1: Q-learning Algorithm – simulated environment – Test Case A – Iteration 1 – Load Averages over Time

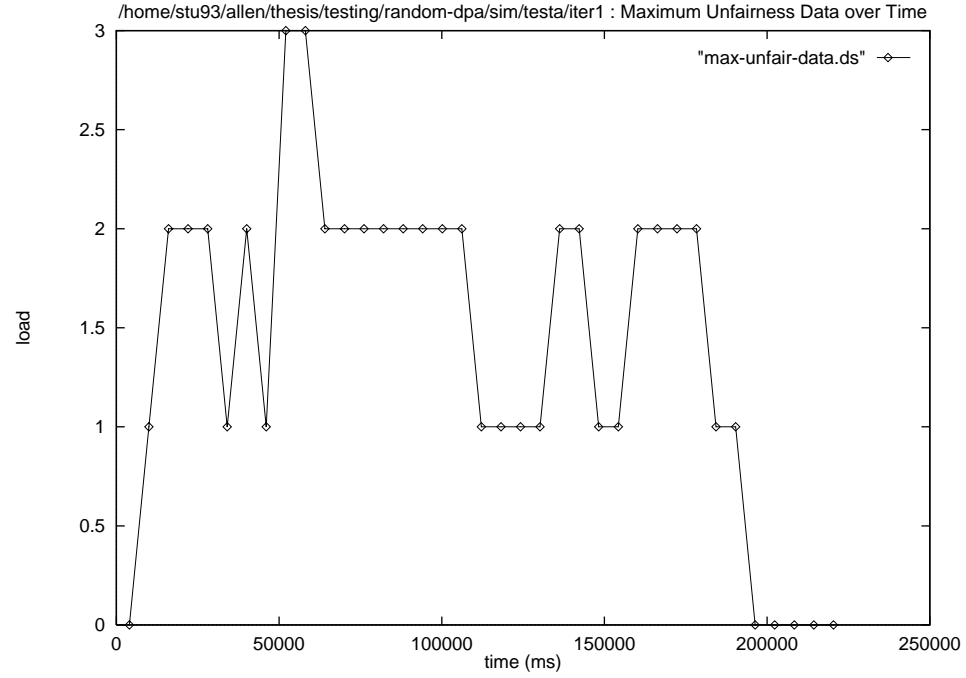


Figure A.2: Q-learning Algorithm – simulated environment – Test Case A – Iteration 1 – Maximum Unfairness over Time

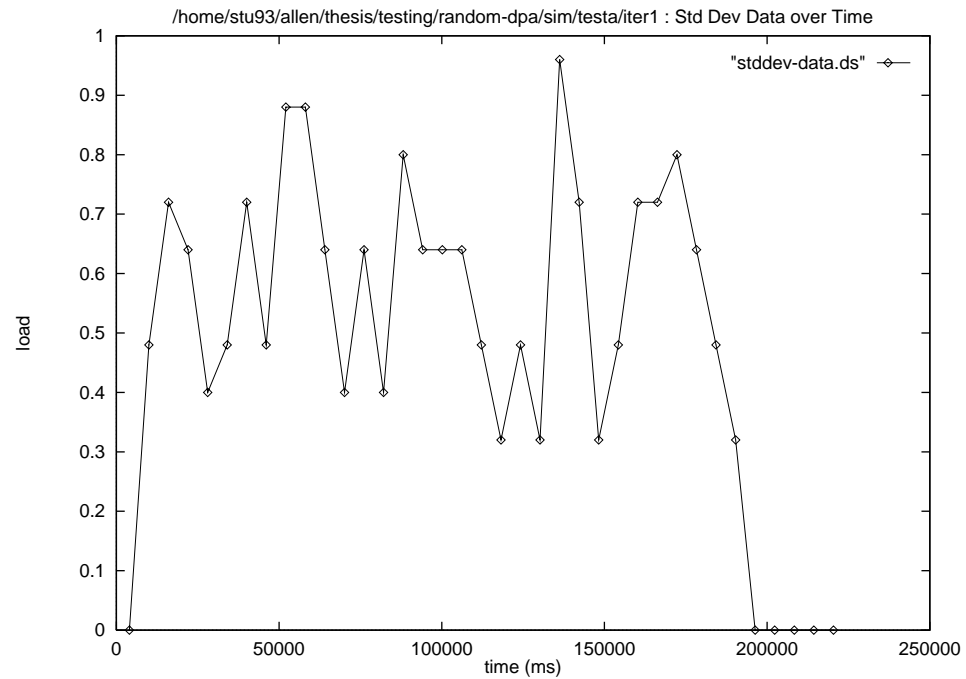


Figure A.3: Q-learning Algorithm – simulated environment – Test Case A – Iteration 1 – Standard Deviation of Loads over Time

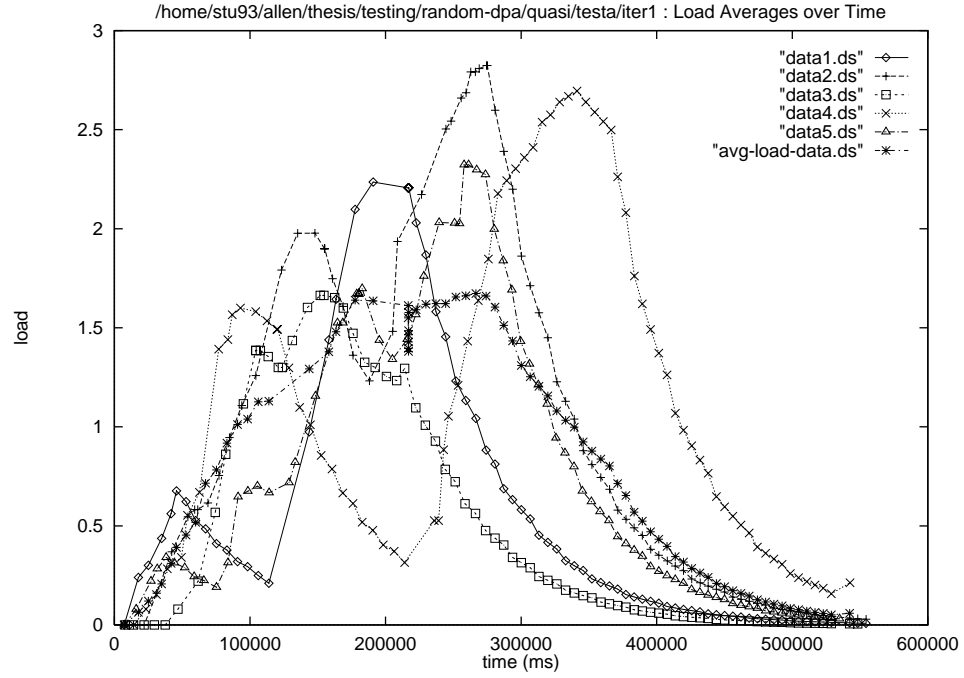


Figure A.4: Q-learning Algorithm – quasi-simulated environment – Test Case A – Iteration 1 – Load Averages over Time

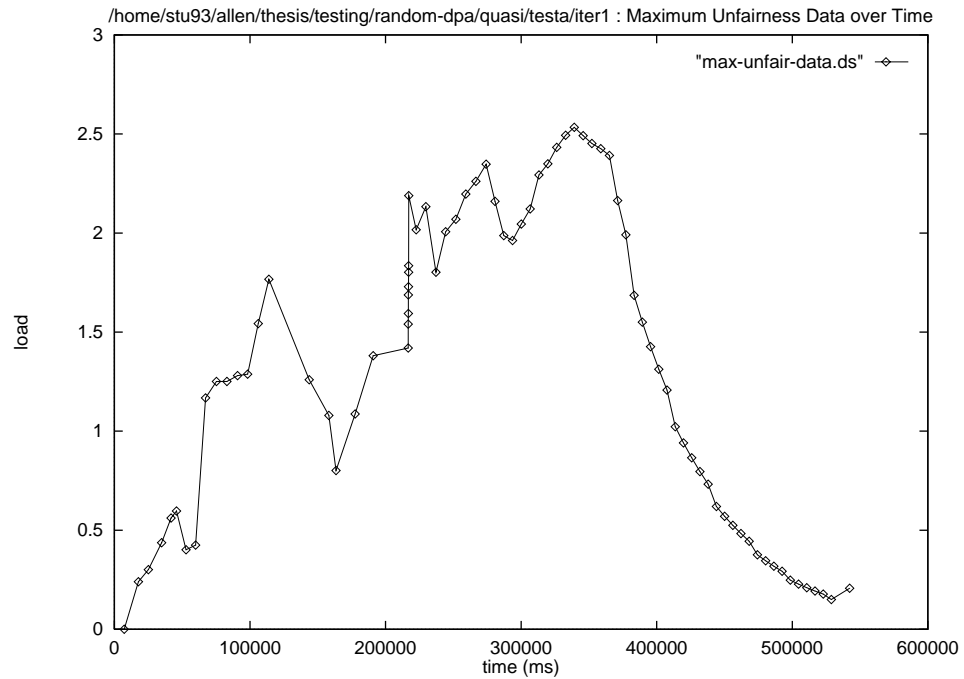


Figure A.5: Q-learning Algorithm – quasi-simulated environment – Test Case A – Iteration 1 – Maximum Unfairness over Time

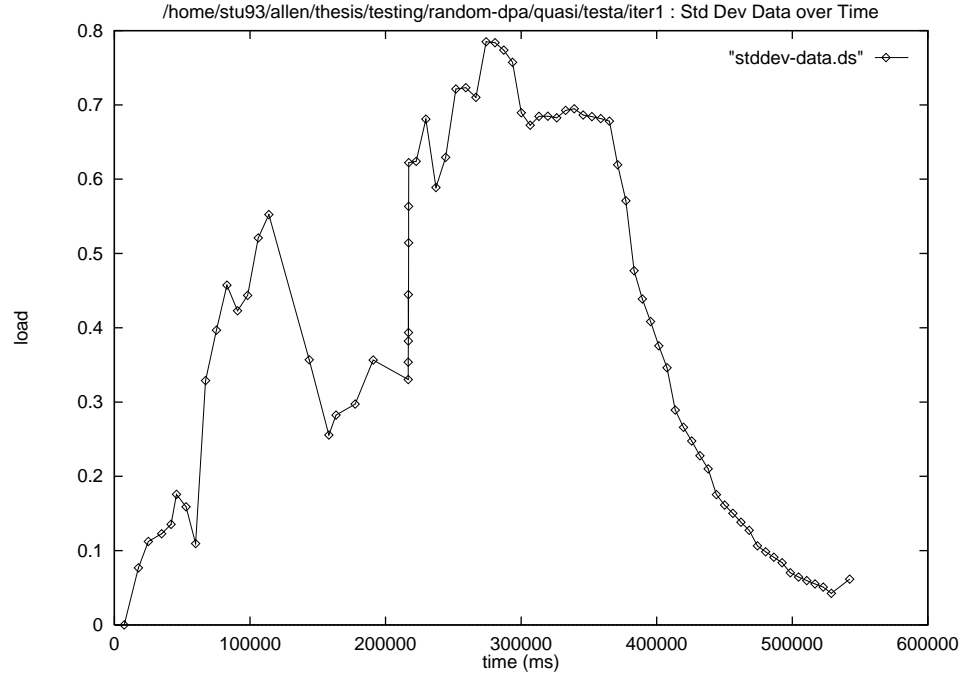


Figure A.6: Q-learning Algorithm – quasi-simulated environment – Test Case A – Iteration 1 – Standard Deviation of Loads over Time

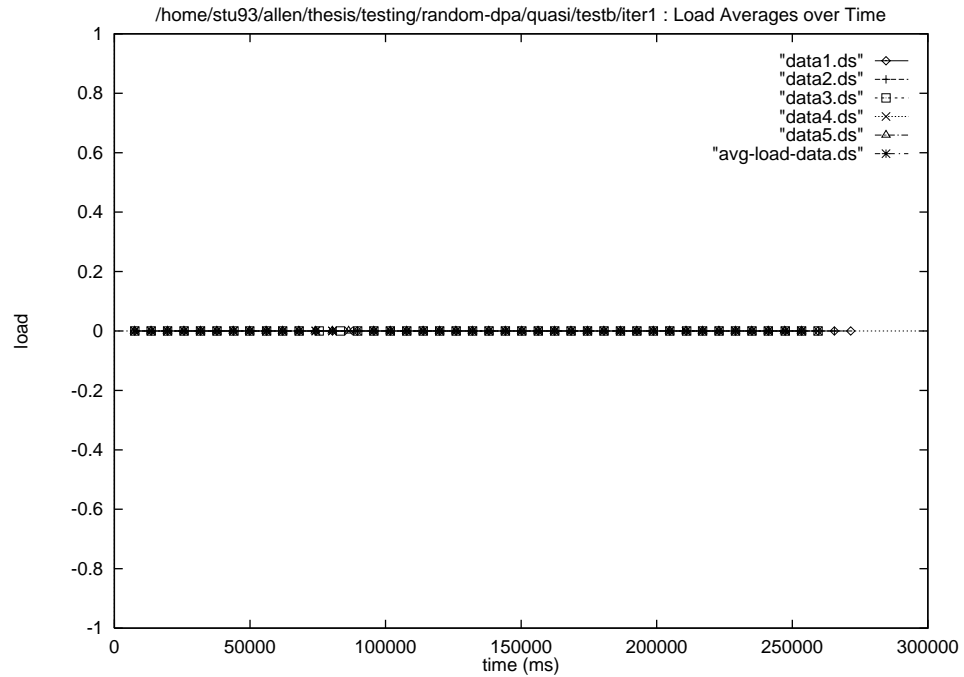


Figure A.7: Q-learning Algorithm – quasi-simulated environment – Test Case B – Iteration 1 – Load Averages over Time

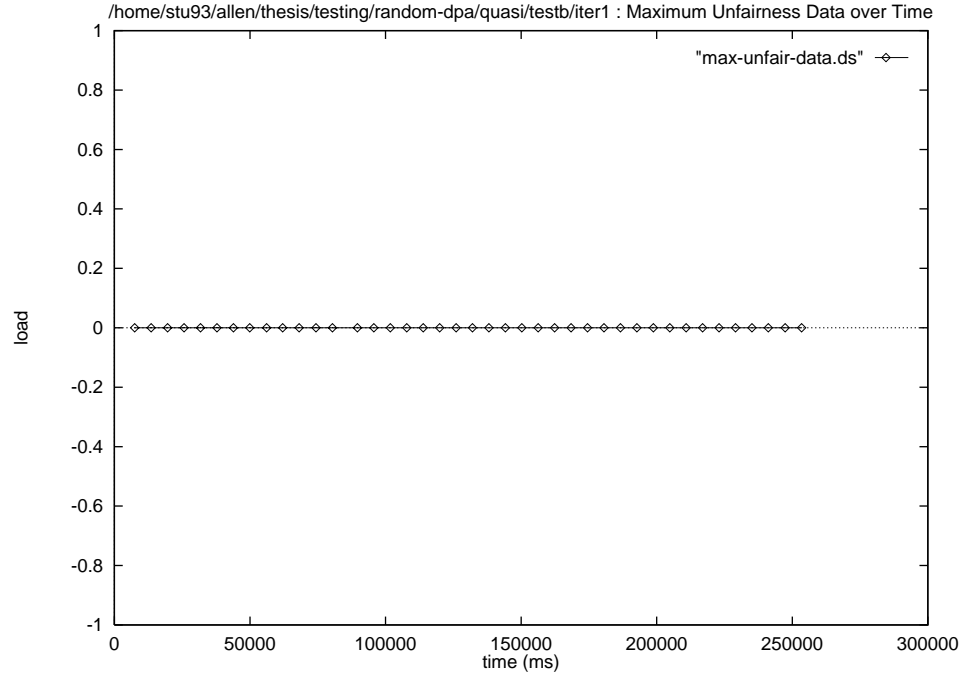


Figure A.8: Q-learning Algorithm – quasi-simulated environment – Test Case B – Iteration 1 – Maximum Unfairness over Time

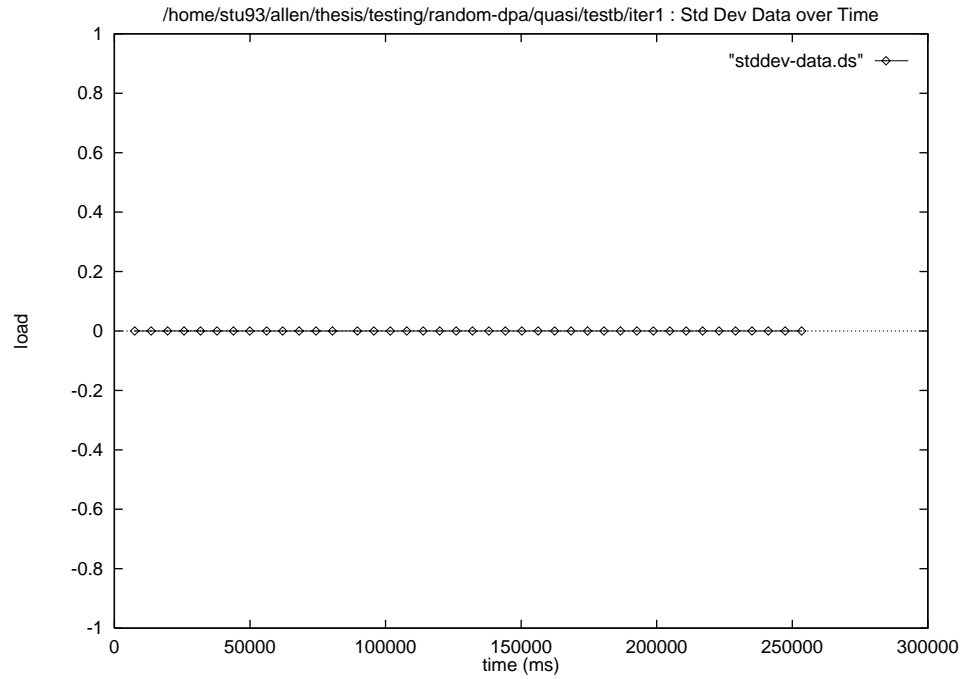


Figure A.9: Q-learning Algorithm – quasi-simulated environment – Test Case B – Iteration 1 – Standard Deviation of Loads over Time

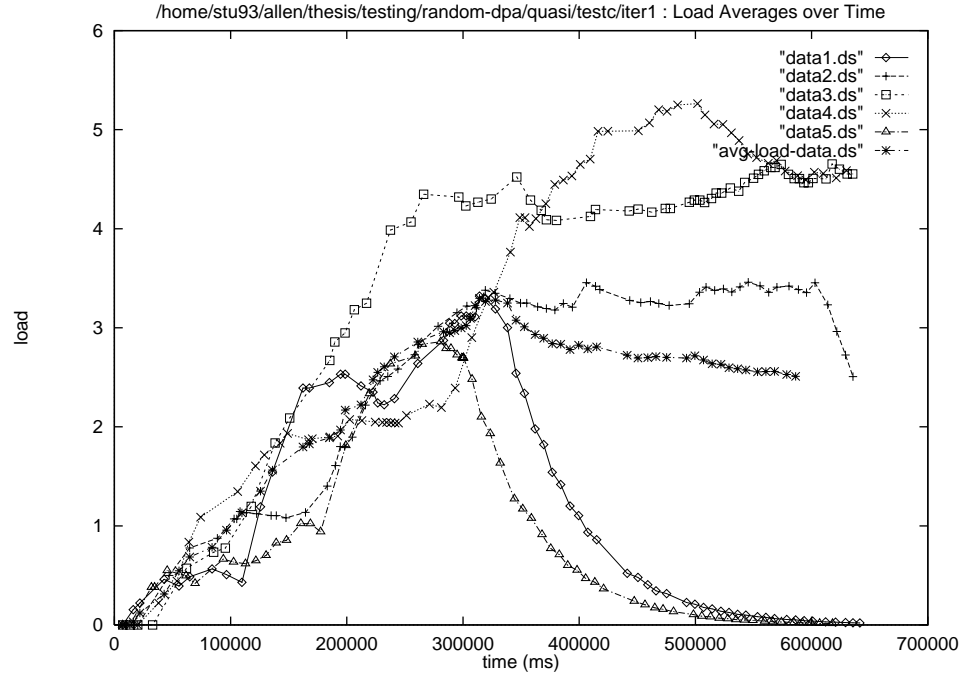


Figure A.10: Q-learning Algorithm – quasi-simulated environment – Test Case C – Iteration 1
– Load Averages over Time

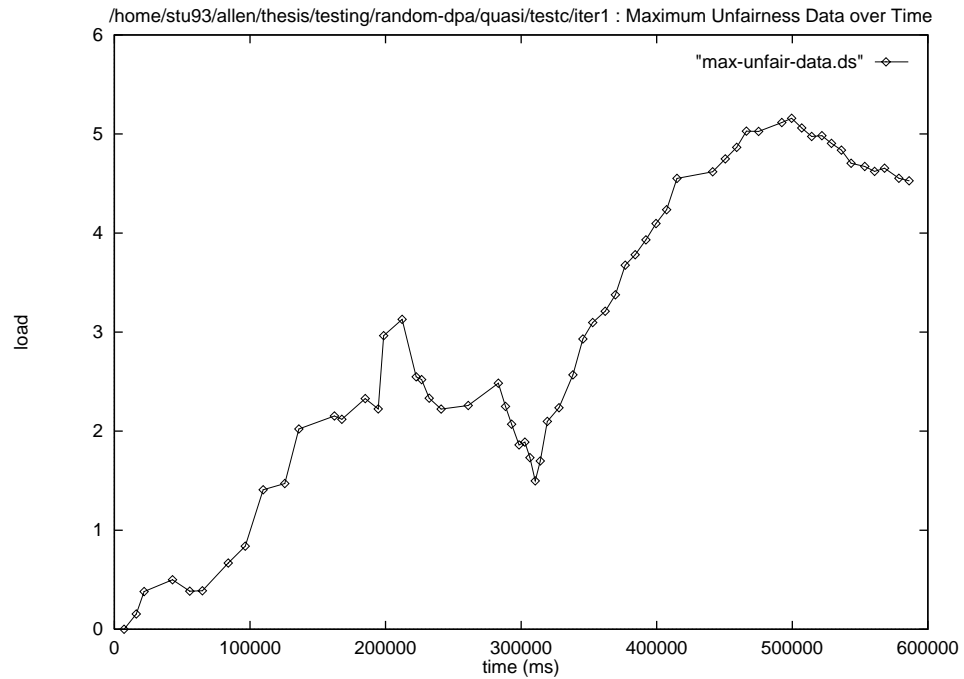


Figure A.11: Q-learning Algorithm – quasi-simulated environment – Test Case C – Iteration 1
– Maximum Unfairness over Time

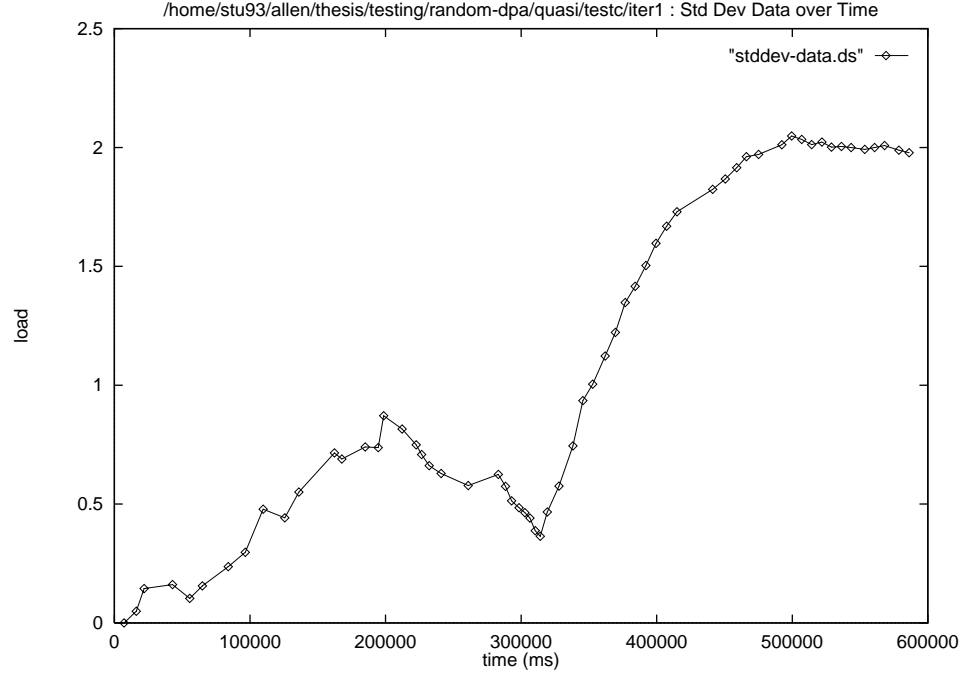


Figure A.12: Q-learning Algorithm – quasi-simulated environment – Test Case C – Iteration 1
– Standard Deviation of Loads over Time

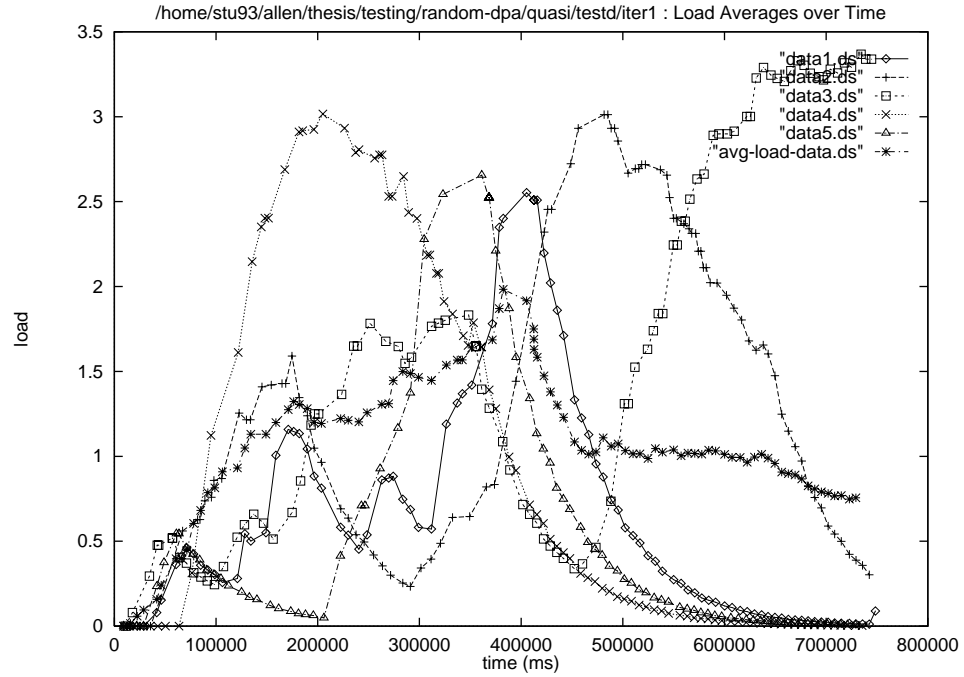


Figure A.13: Q-learning Algorithm – quasi-simulated environment – Test Case D – Iteration 1
– Load Averages over Time

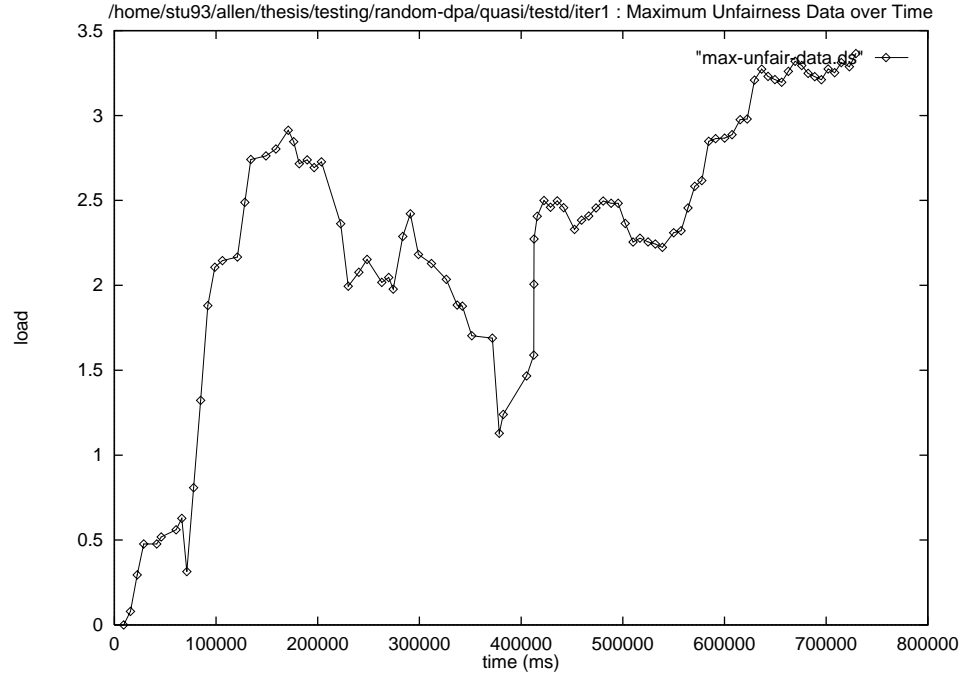


Figure A.14: Q-learning Algorithm – quasi-simulated environment – Test Case D – Iteration 1
– Maximum Unfairness over Time

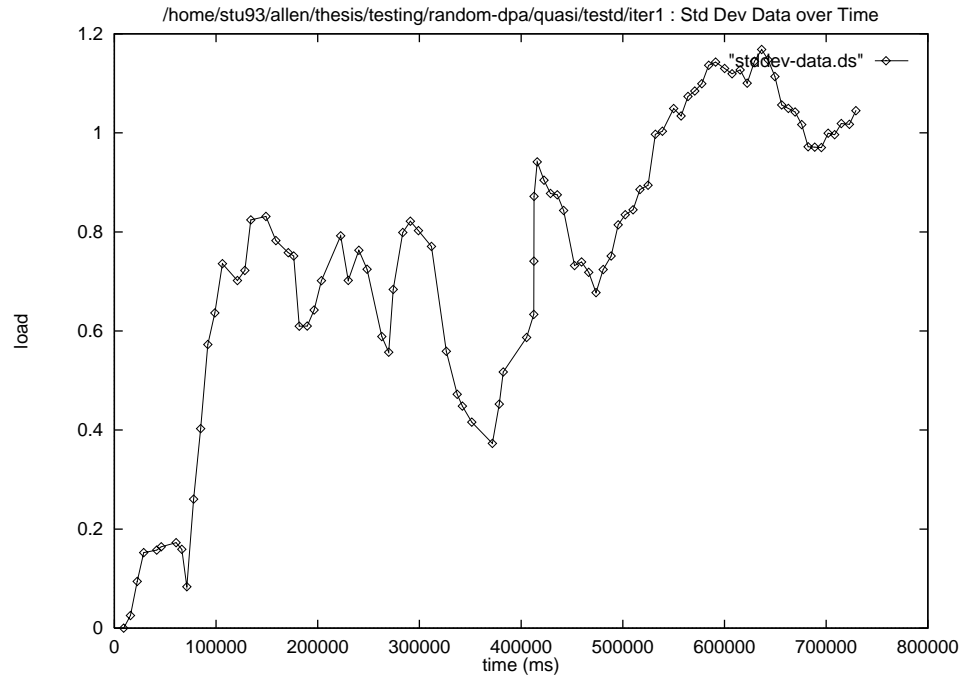


Figure A.15: Q-learning Algorithm – quasi-simulated environment – Test Case D – Iteration 1
– Standard Deviation of Loads over Time

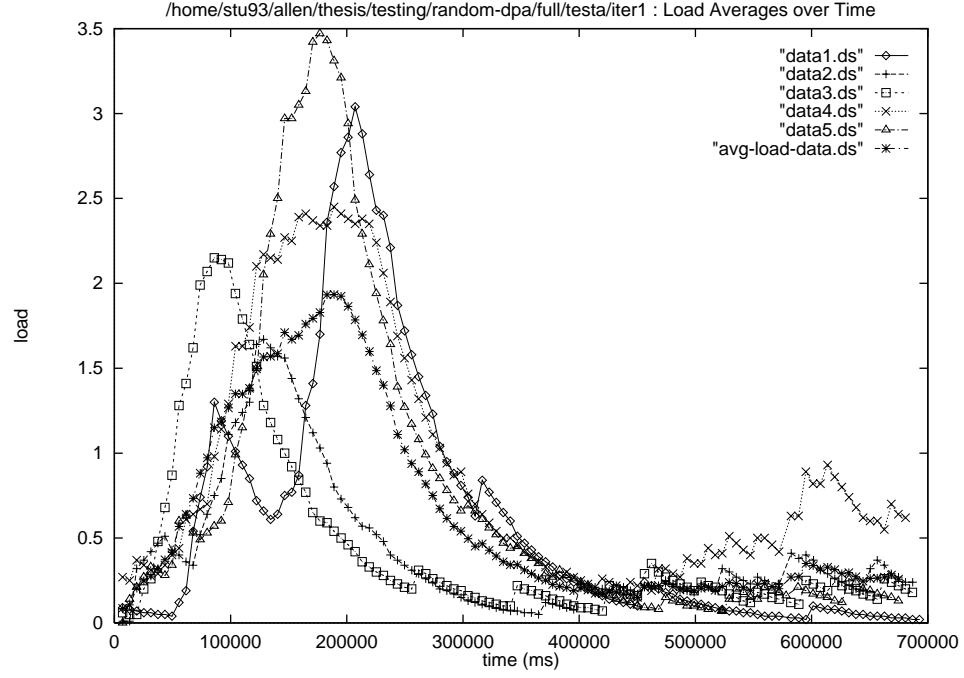


Figure A.16: Q-learning Algorithm – Full implementation – Test Case A – Iteration 1 – Load Averages over Time

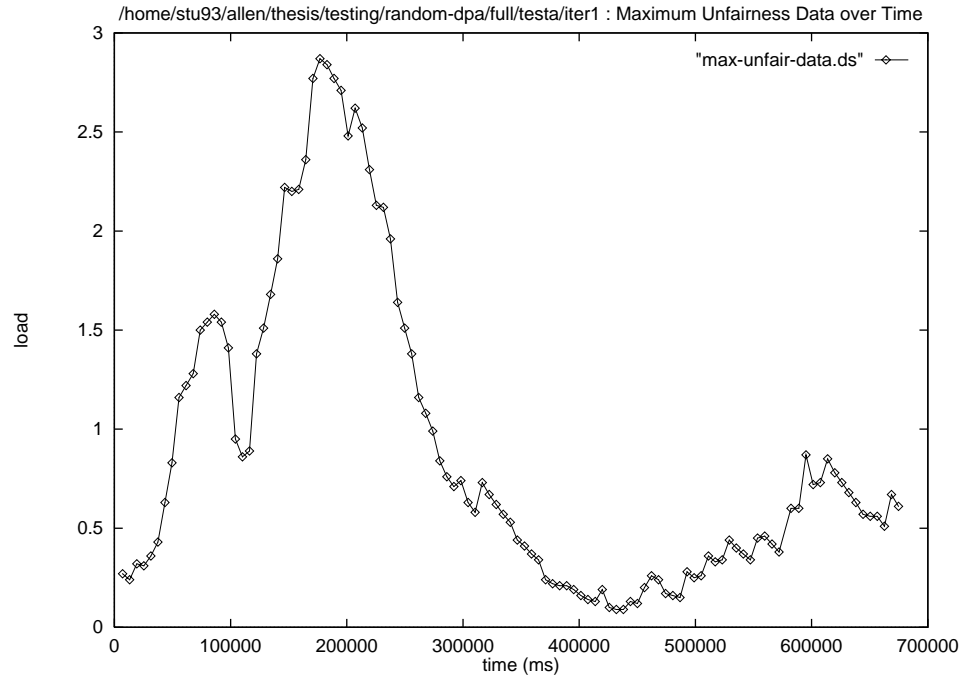


Figure A.17: Q-learning Algorithm – Full implementation – Test Case A – Iteration 1 – Maximum Unfairness over Time

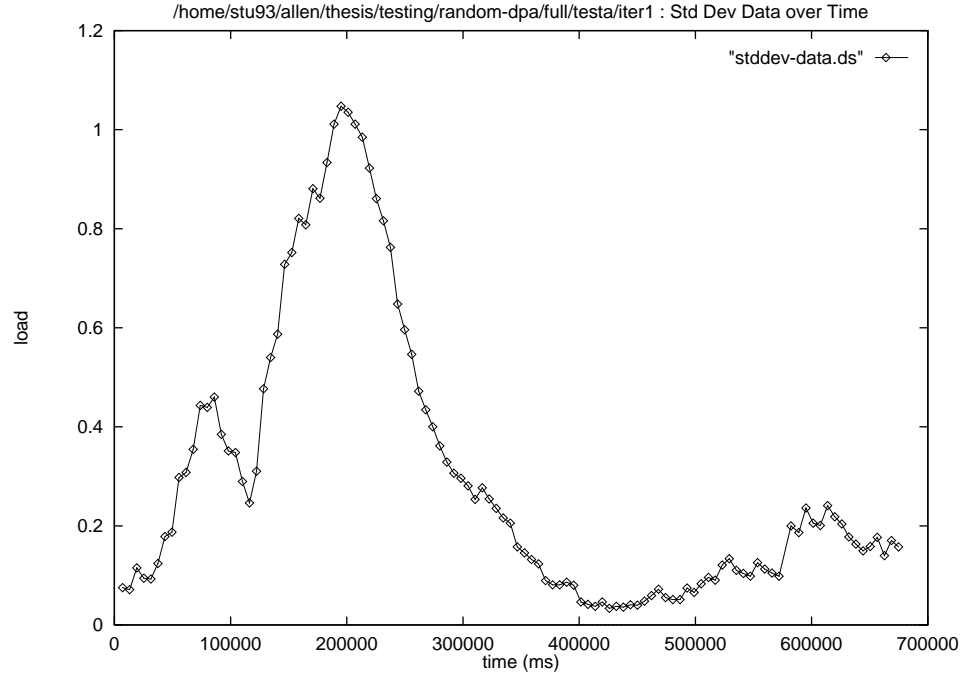


Figure A.18: Q-learning Algorithm – Full implementation – Test Case A – Iteration 1 – Standard Deviation of Loads over Time

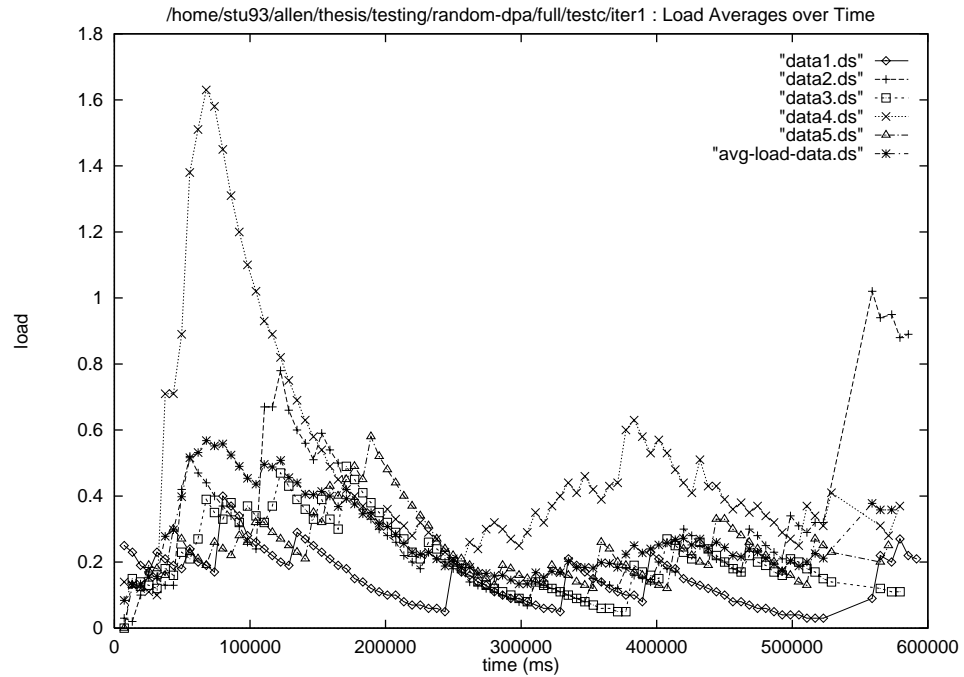


Figure A.19: Q-learning Algorithm – Full implementation – Test Case C – Iteration 1 – Load Averages over Time

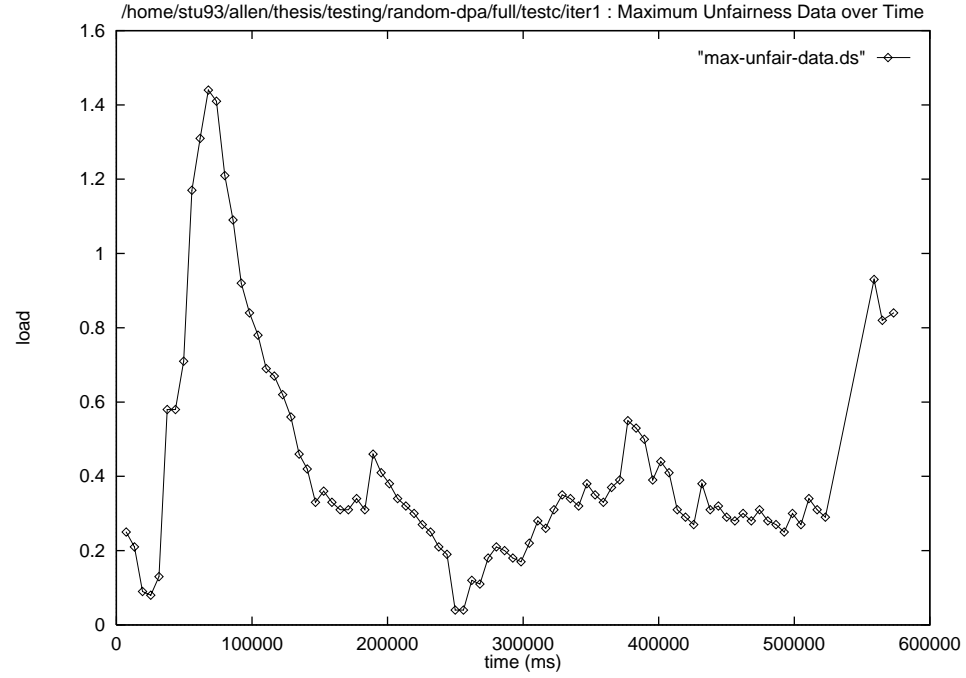


Figure A.20: Q-learning Algorithm – Full implementation – Test Case C – Iteration 1 – Maximum Unfairness over Time

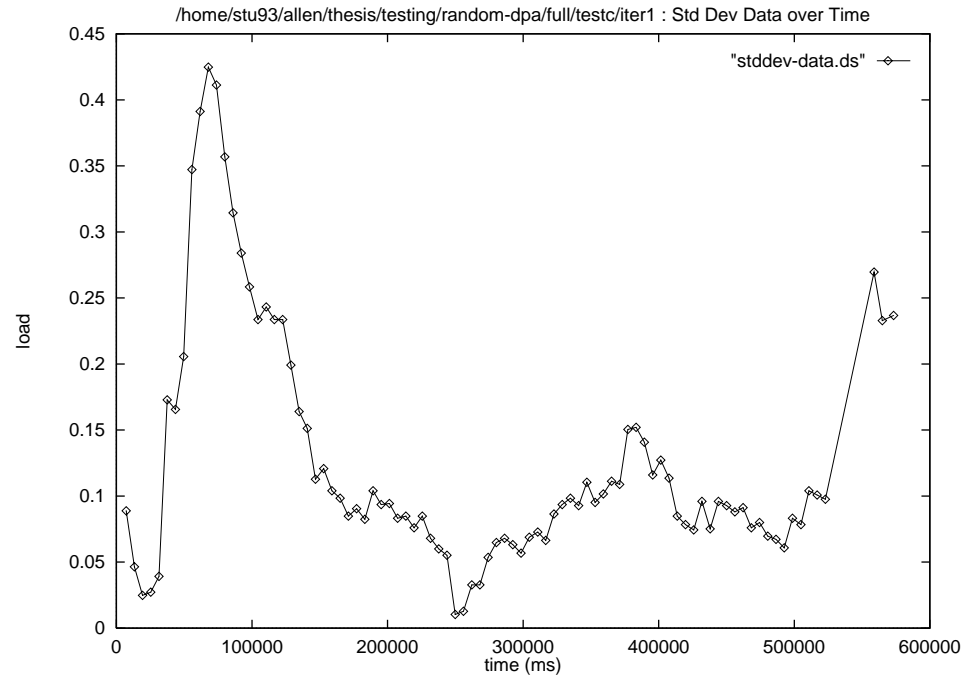


Figure A.21: Q-learning Algorithm – Full implementation – Test Case C – Iteration 1 – Standard Deviation of Loads over Time

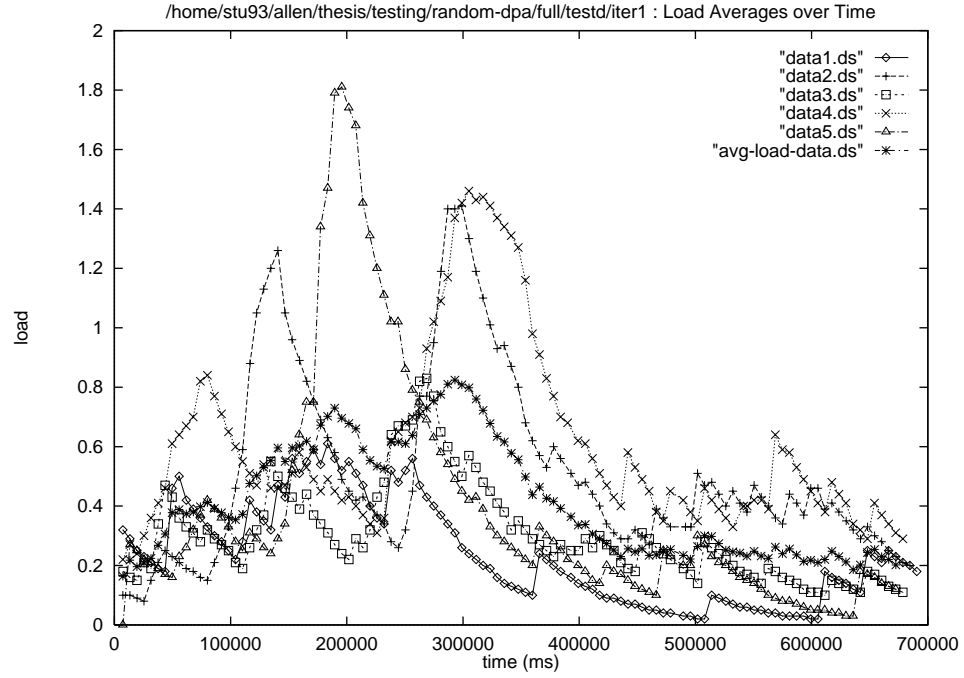


Figure A.22: Q-learning Algorithm – Full implementation – Test Case D – Iteration 1 – Load Averages over Time

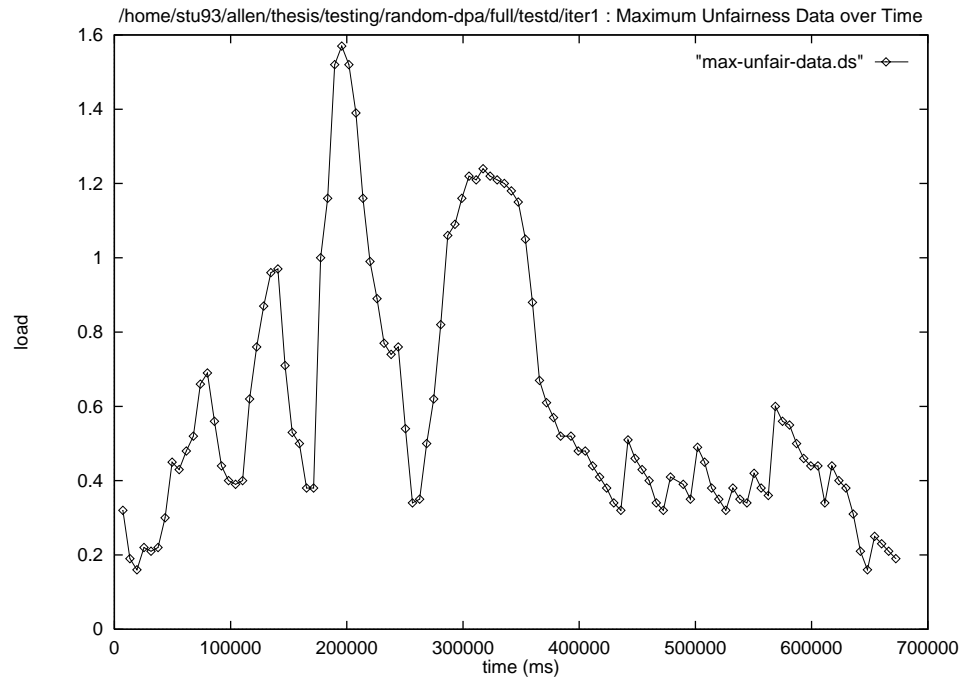


Figure A.23: Q-learning Algorithm – Full implementation – Test Case D – Iteration 1 – Maximum Unfairness over Time

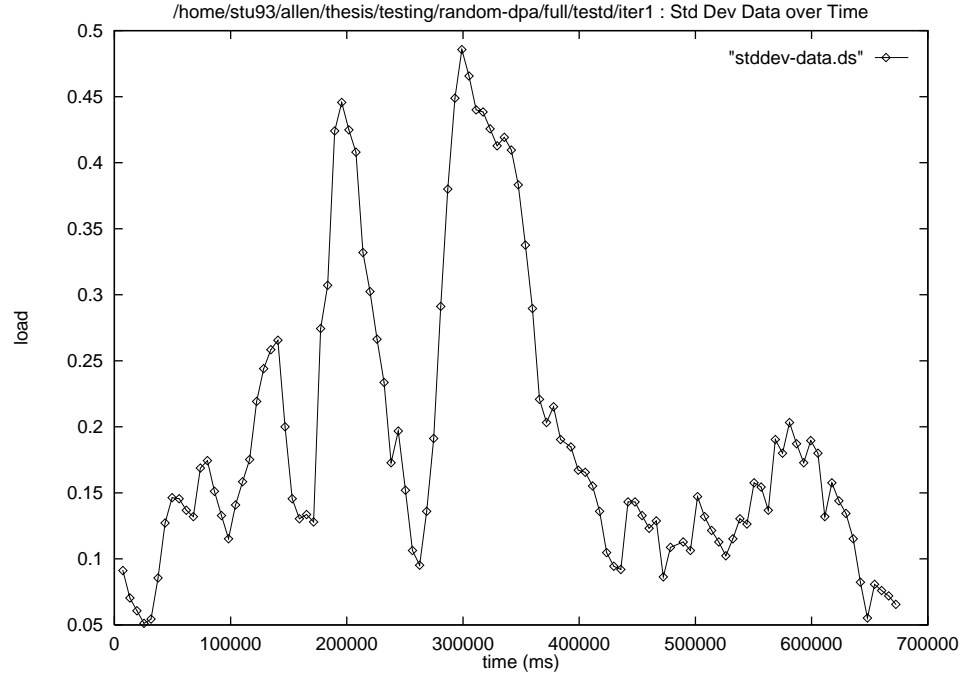


Figure A.24: Q-learning Algorithm – Full implementation – Test Case D – Iteration 1 – Standard Deviation of Loads over Time

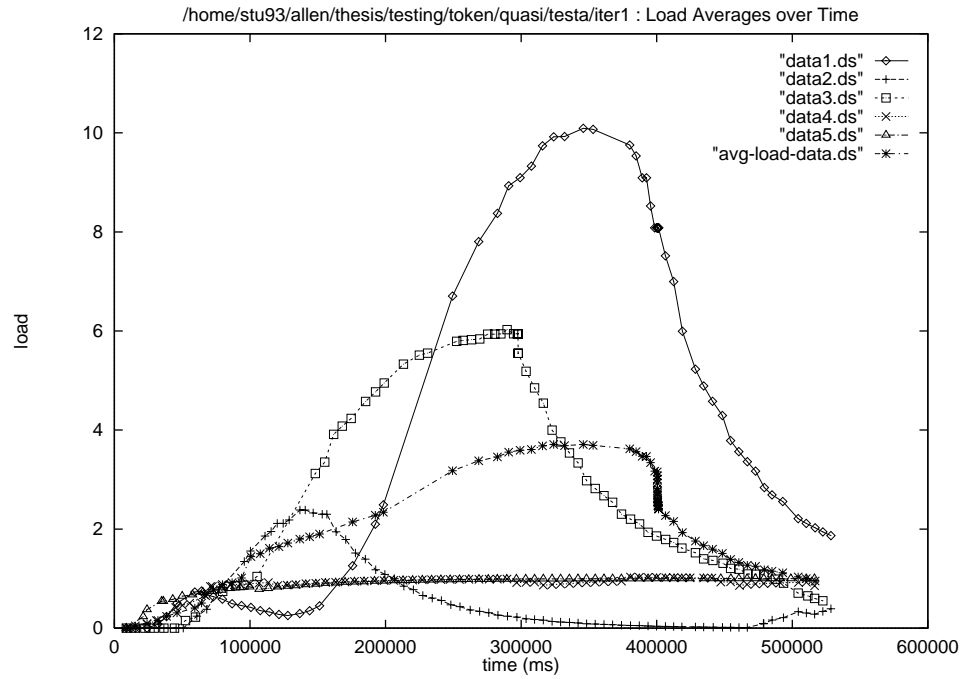


Figure A.25: Token-based Algorithm – quasi-simulated environment – Test Case A – Iteration 1 – Load Averages over Time

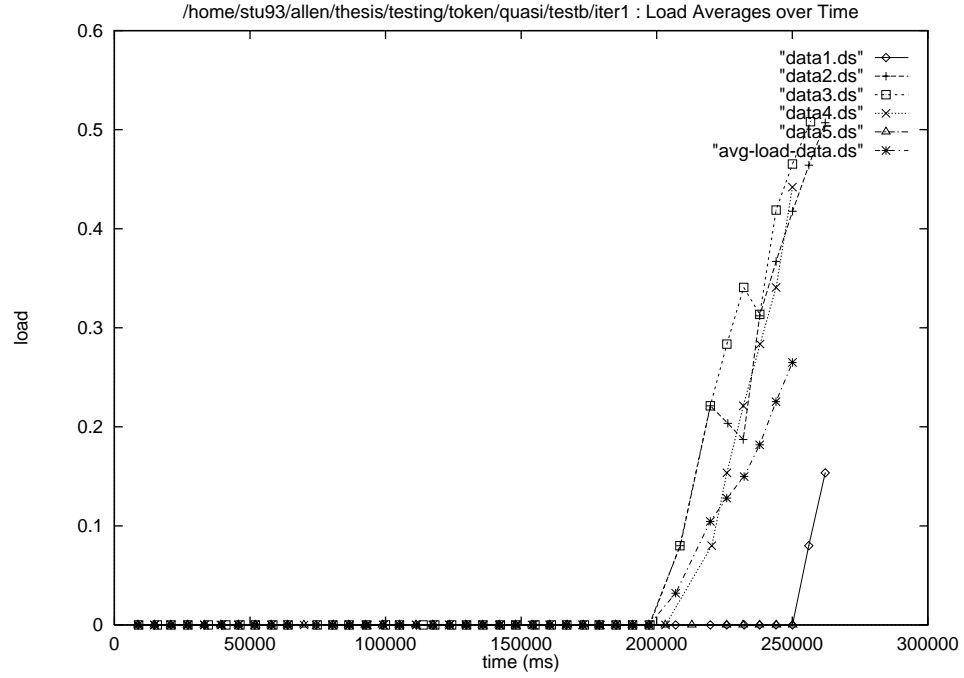


Figure A.26: Token-based Algorithm – quasi-simulated environment – Test Case B – Iteration

1 – Load Averages over Time

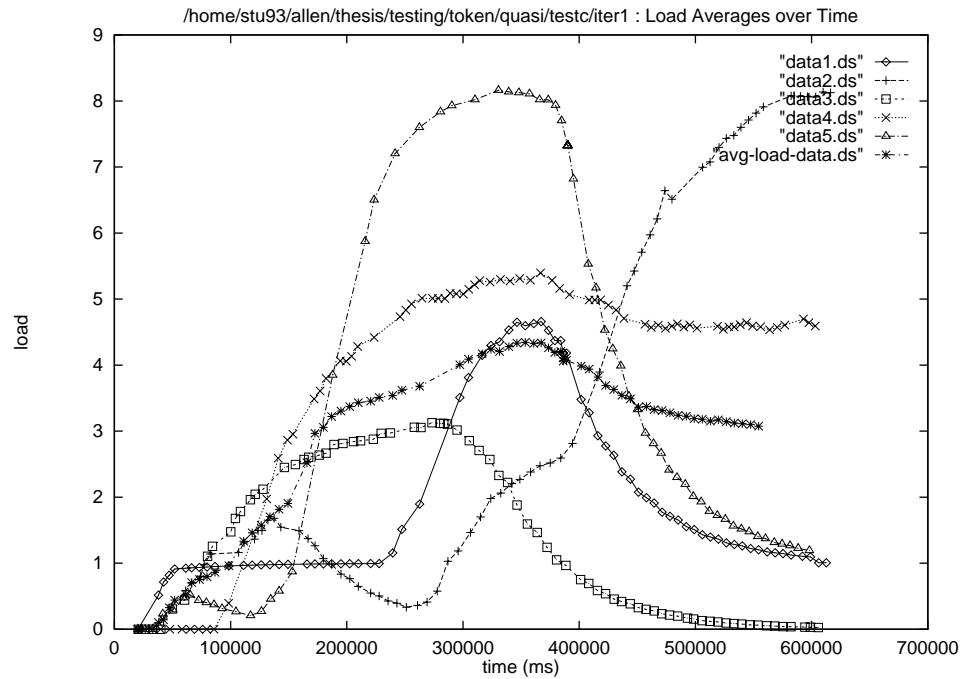


Figure A.27: Token-based Algorithm – quasi-simulated environment – Test Case C – Iteration

1 – Load Averages over Time

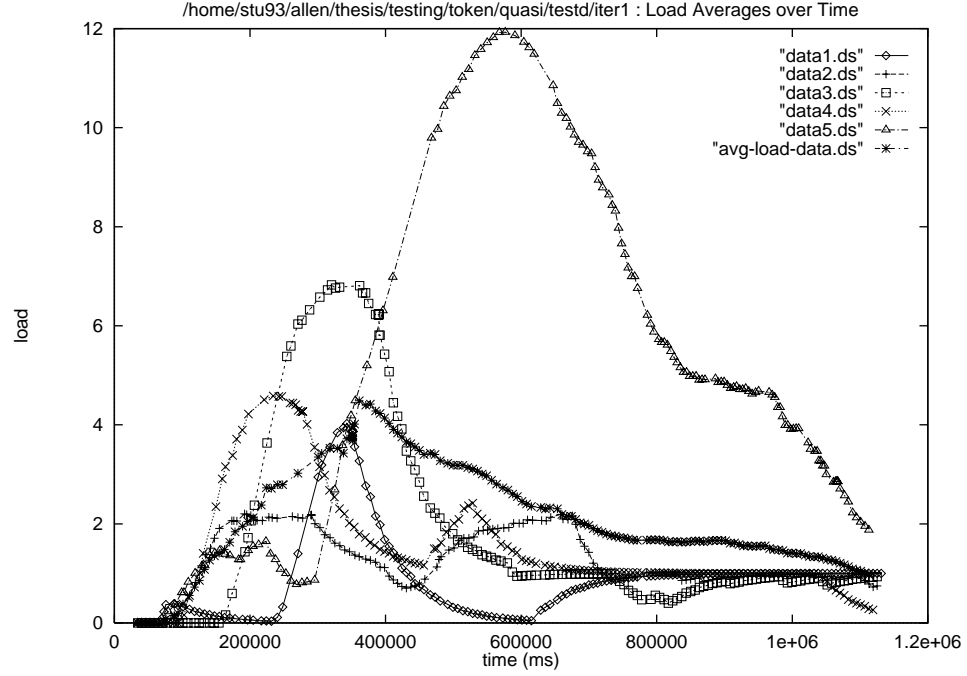


Figure A.28: Token-based Algorithm – quasi-simulated environment – Test Case D – Iteration

1 – Load Averages over Time

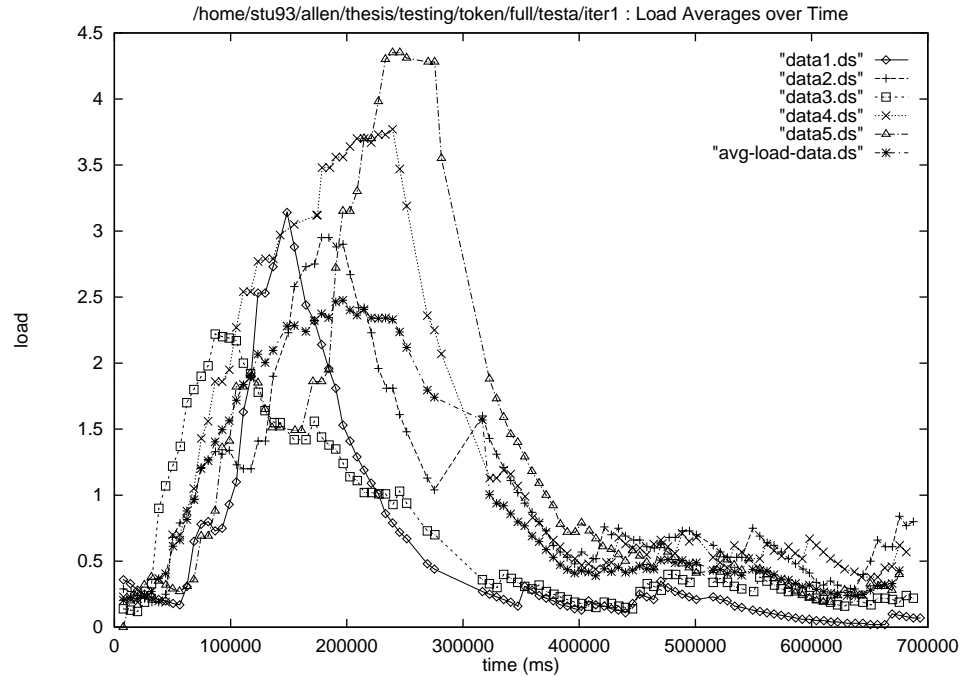


Figure A.29: Token-based Algorithm – Full implementation – Test Case A – Iteration 1 – Load

Averages over Time

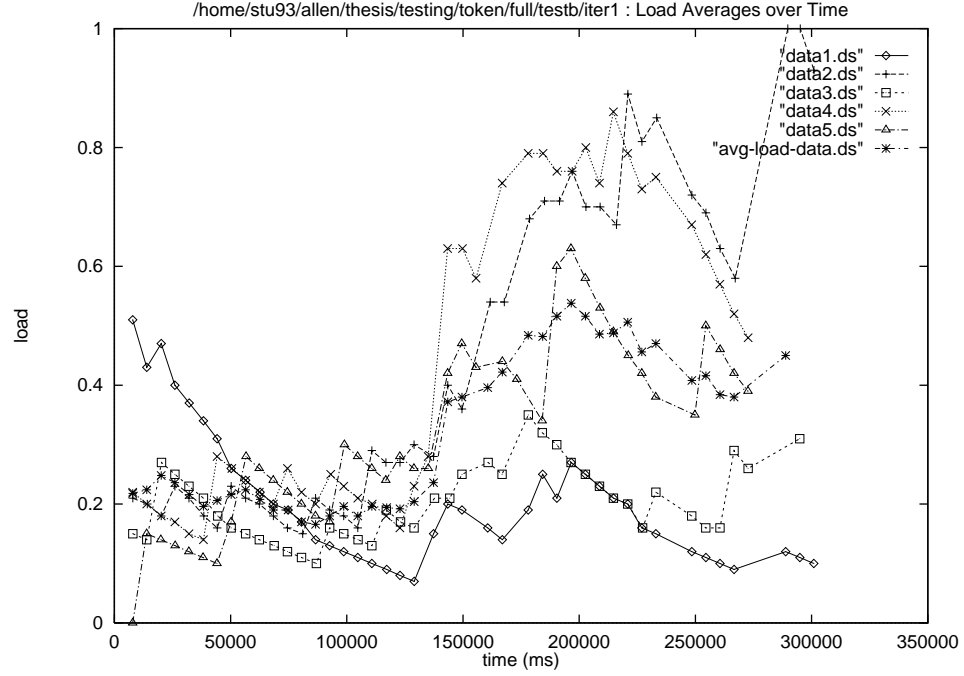


Figure A.30: Token-based Algorithm – Full implementation – Test Case B – Iteration 1 – Load Averages over Time

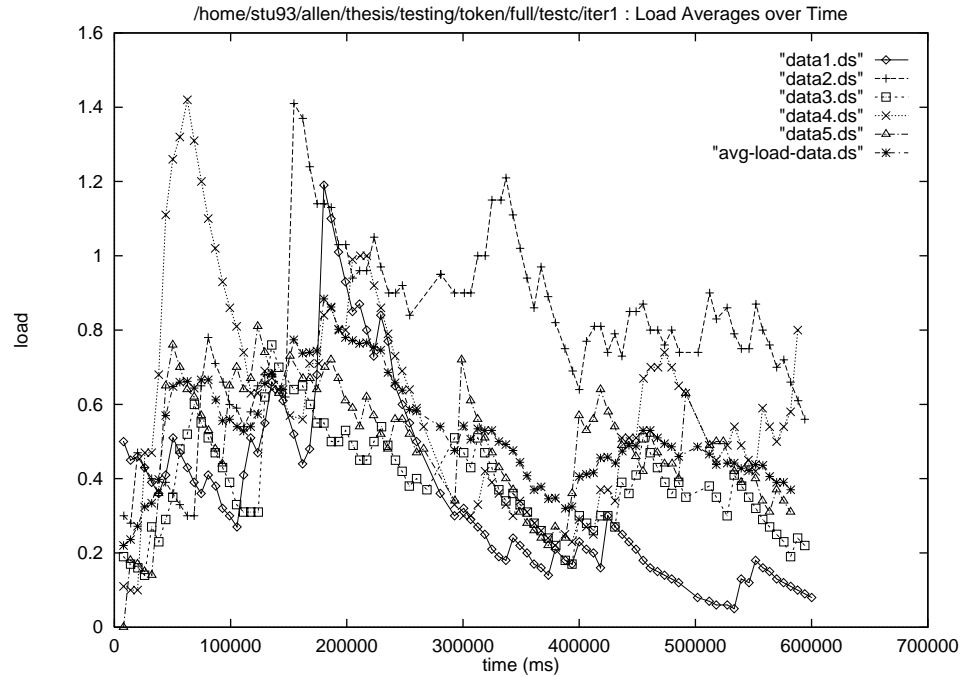


Figure A.31: Token-based Algorithm – Full implementation – Test Case C – Iteration 1 – Load Averages over Time

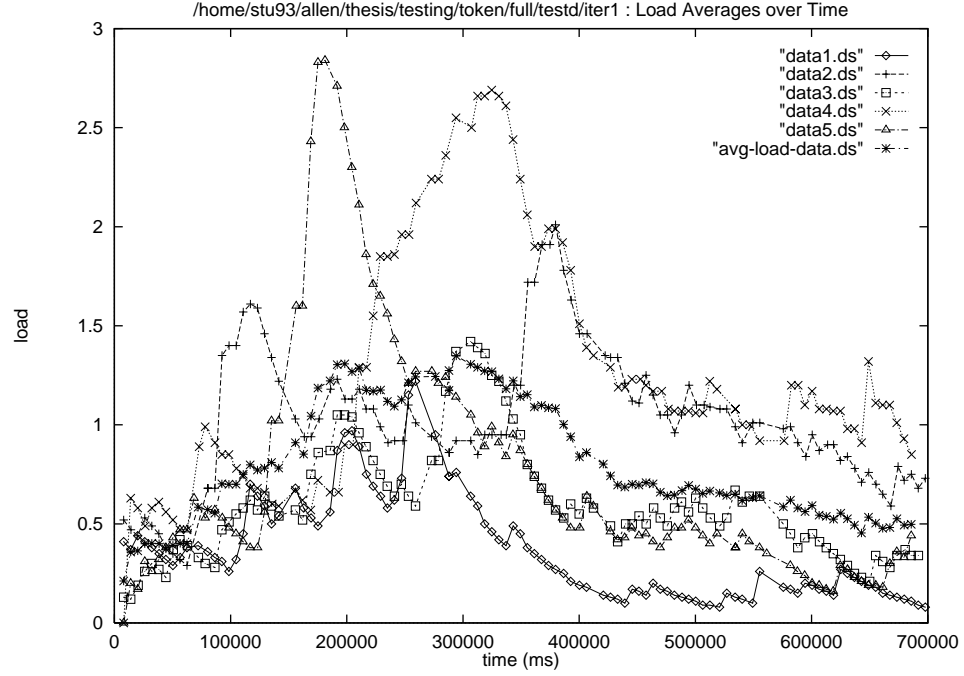


Figure A.32: Token-based Algorithm – Full implementation – Test Case D – Iteration 1 – Load Averages over Time

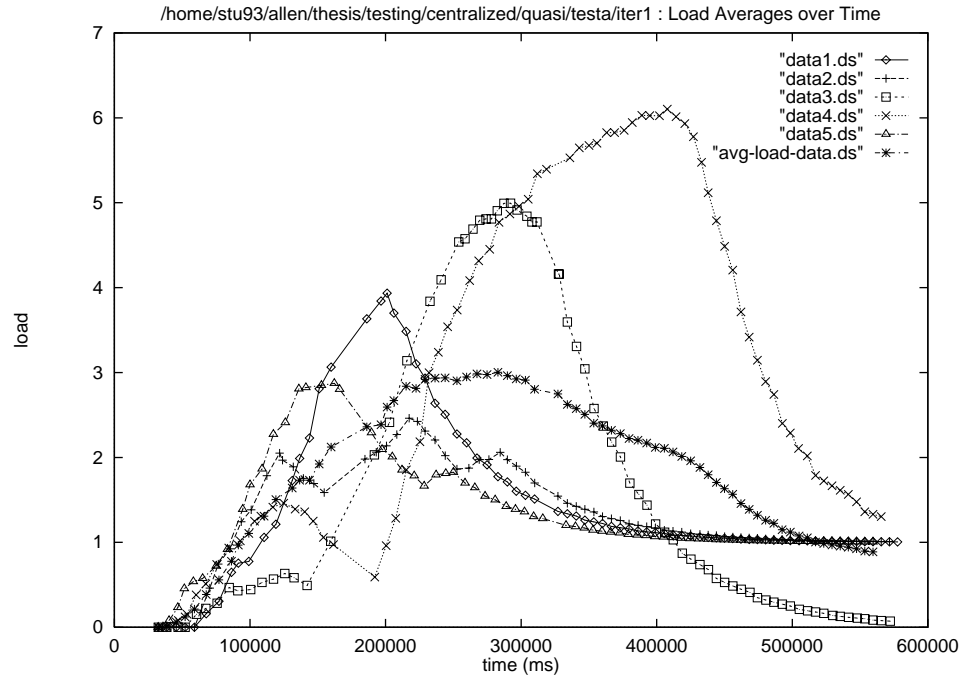


Figure A.33: Centralized Algorithm – quasi-simulated environment – Test Case A – Iteration 1 – Load Averages over Time

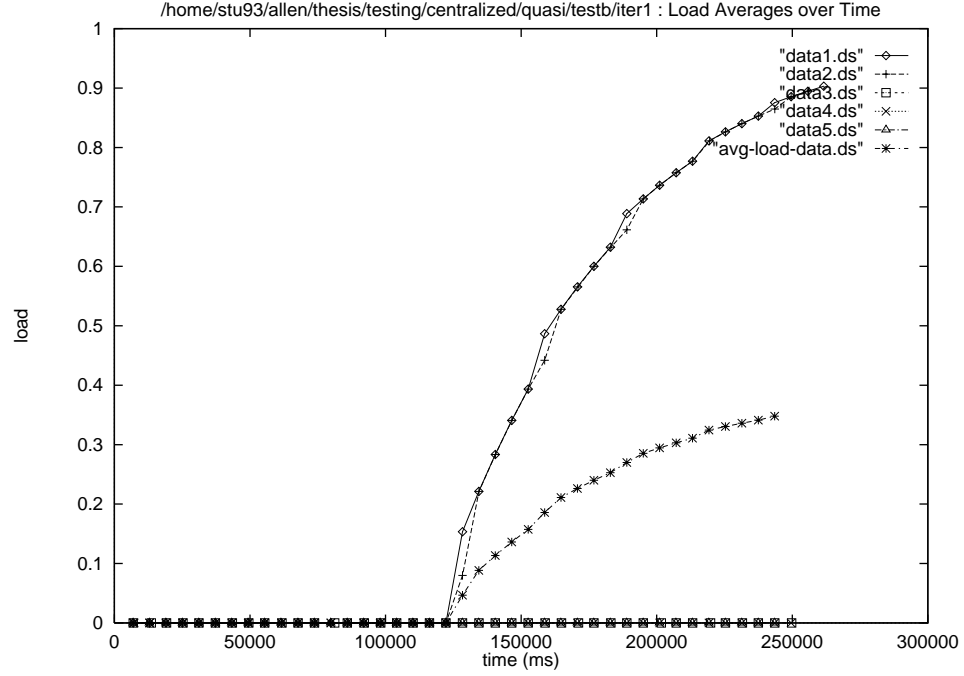


Figure A.34: Centralized Algorithm – quasi-simulated environment – Test Case B – Iteration 1
– Load Averages over Time

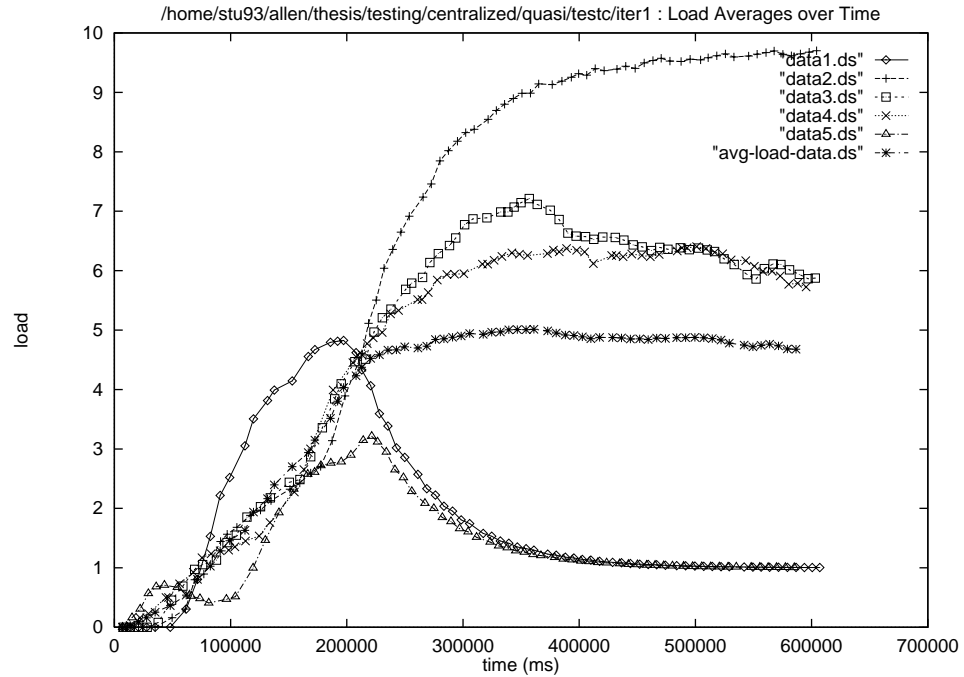


Figure A.35: Centralized Algorithm – quasi-simulated environment – Test Case C – Iteration 1
– Load Averages over Time

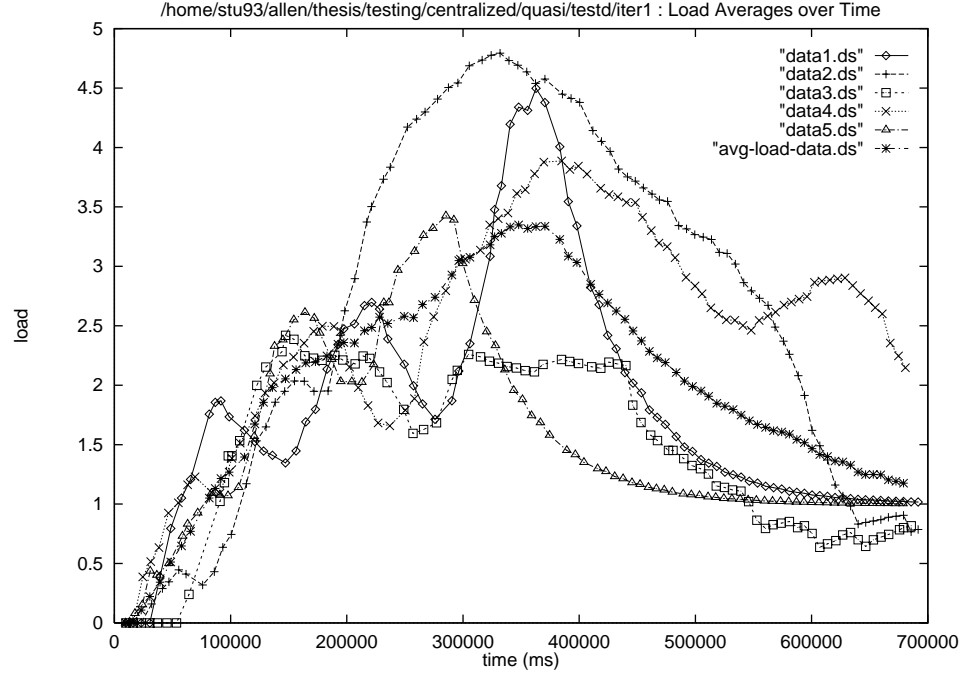


Figure A.36: Centralized Algorithm – quasi-simulated environment – Test Case D – Iteration 1
– Load Averages over Time

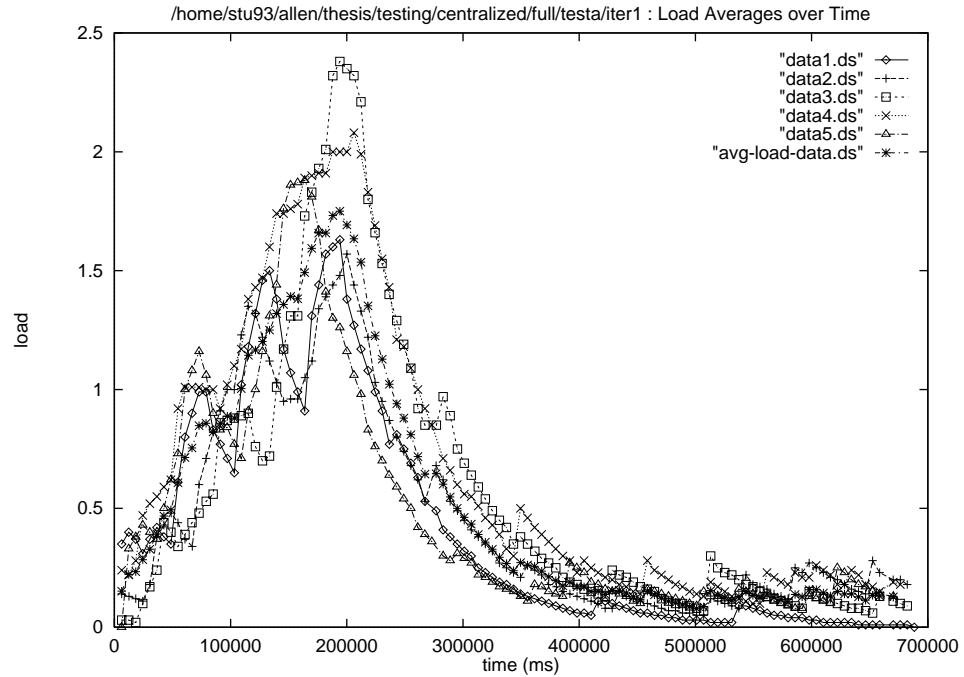


Figure A.37: Centralized Algorithm – Full implementation – Test Case A – Iteration 1 – Load
Averages over Time

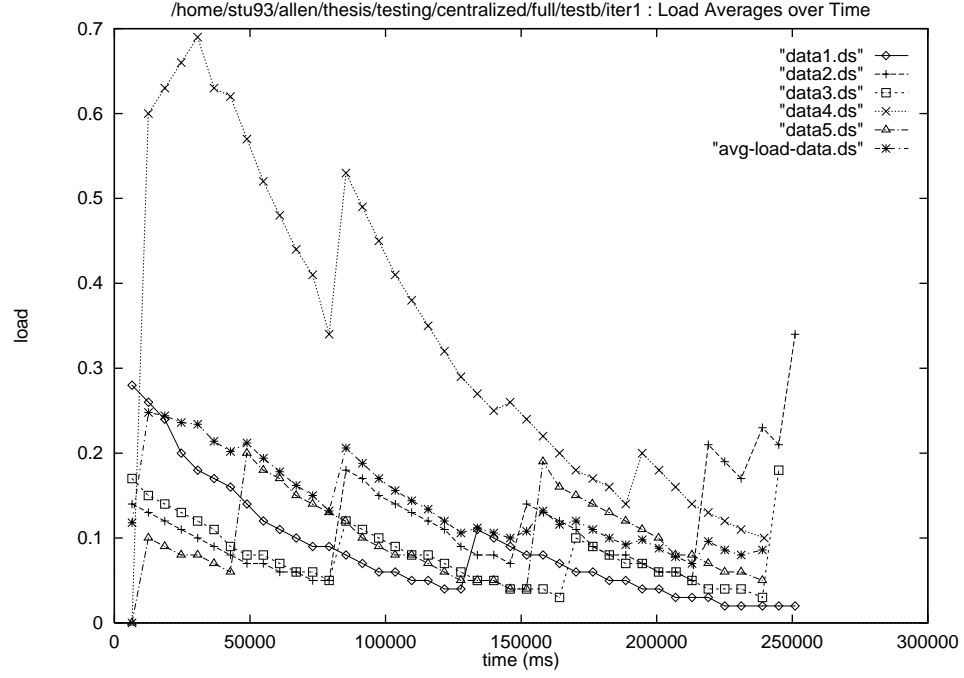


Figure A.38: Centralized Algorithm – Full implementation – Test Case B – Iteration 1 – Load Averages over Time

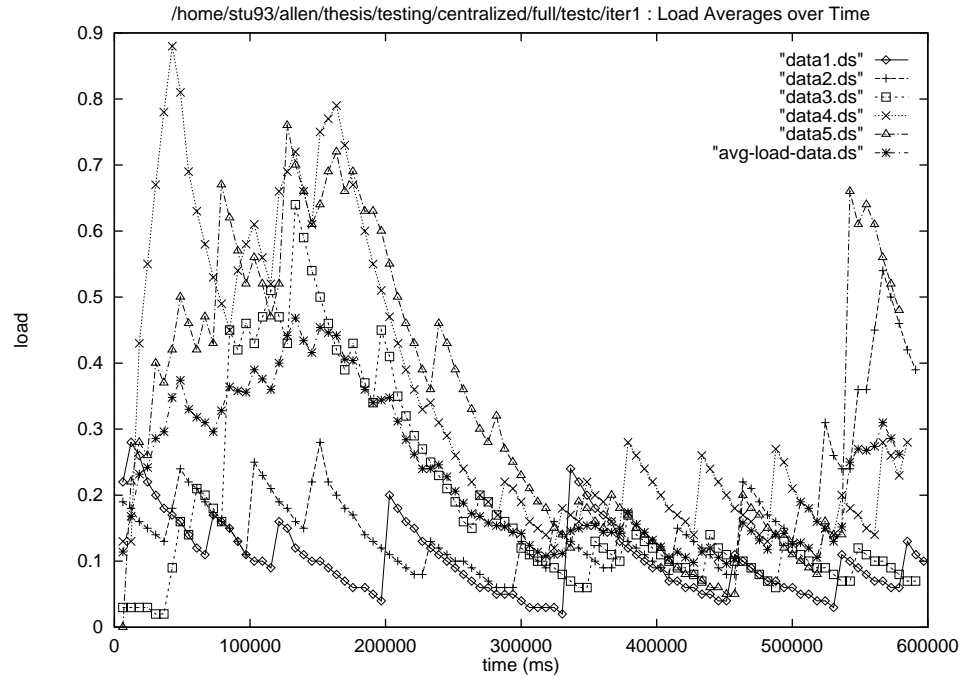


Figure A.39: Centralized Algorithm – Full implementation – Test Case C – Iteration 1 – Load Averages over Time

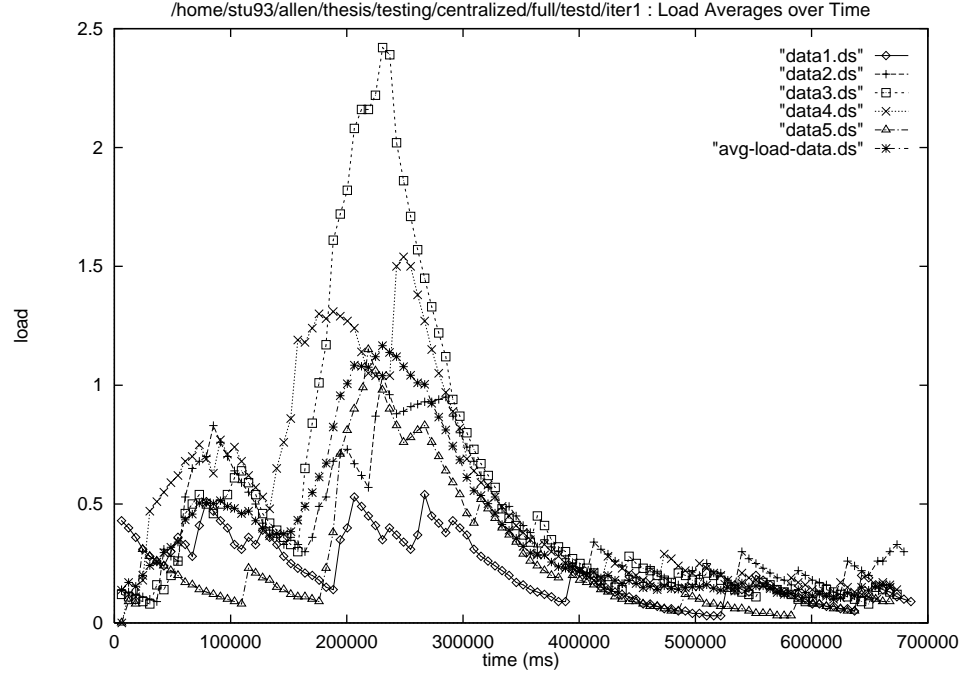


Figure A.40: Centralized Algorithm – Full implementation – Test Case D – Iteration 1 – Load Averages over Time

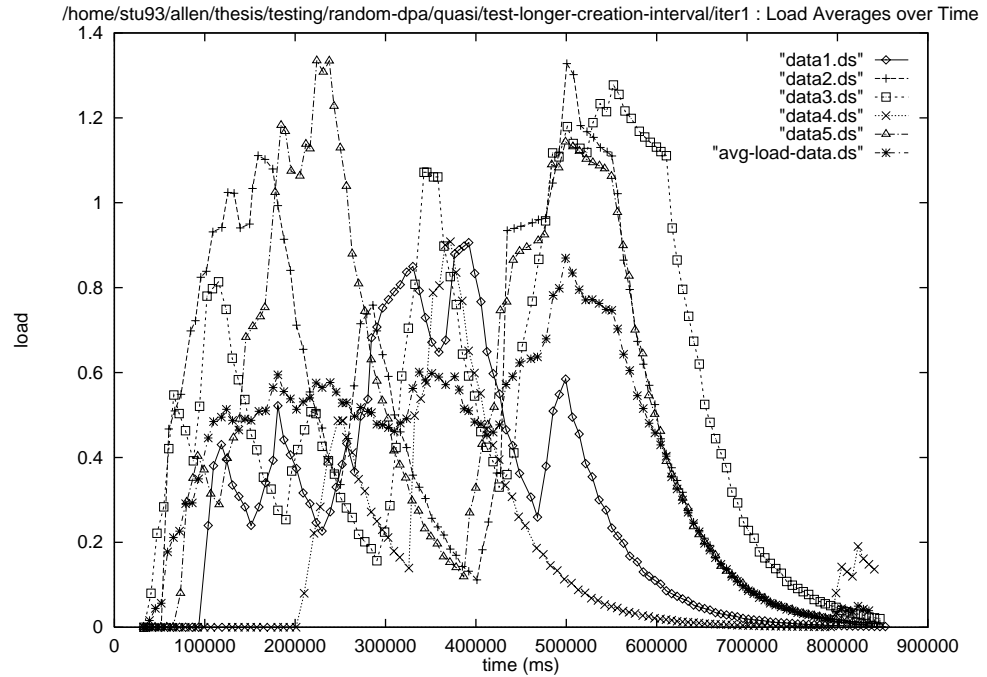


Figure A.41: Q-learning Algorithm – Quasi-simulated environment – Test Case : Longer Creation Interval – Iteration 1 – Load Averages over Time

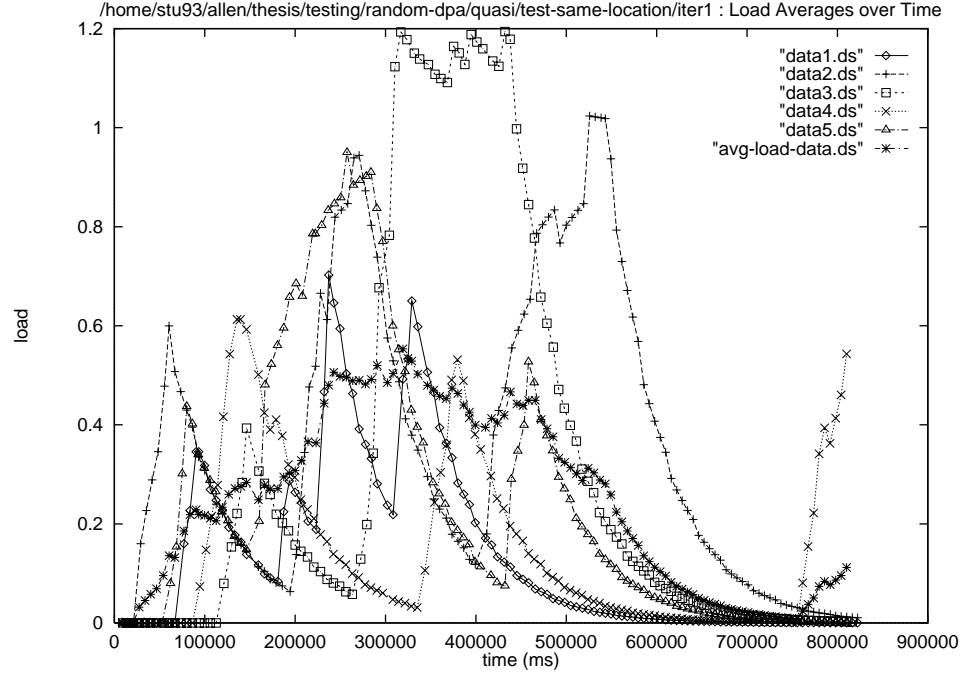


Figure A.42: Q-learning Algorithm – Quasi-simulated environment – Test Case : Test Same Creation Location – Iteration 1 – Load Averages over Time

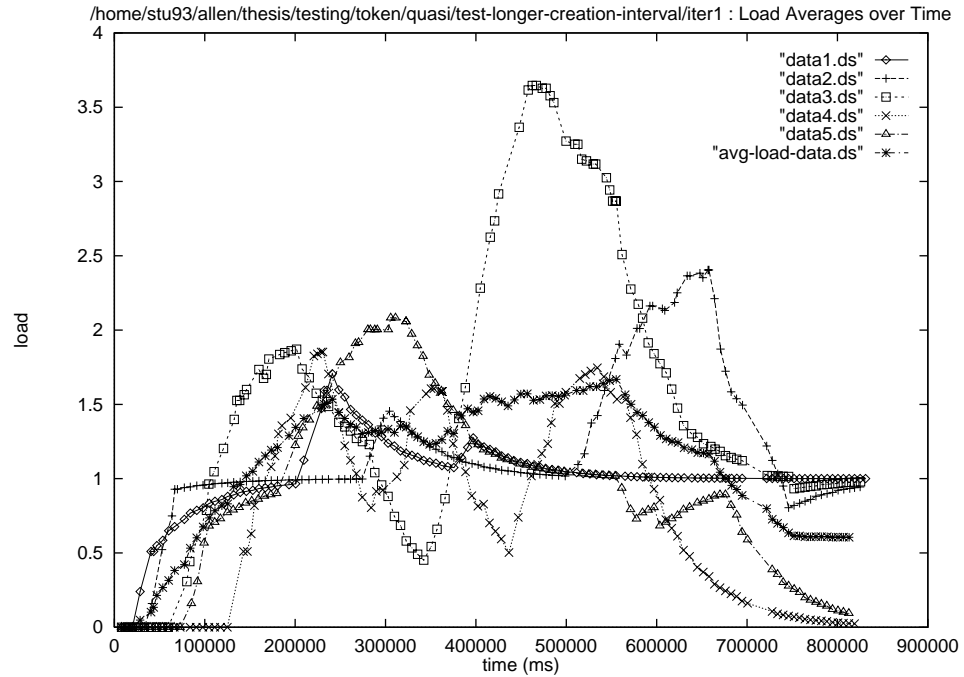


Figure A.43: Token-based Algorithm – Quasi-simulated environment – Test Case : Longer Creation Interval – Iteration 1 – Load Averages over Time

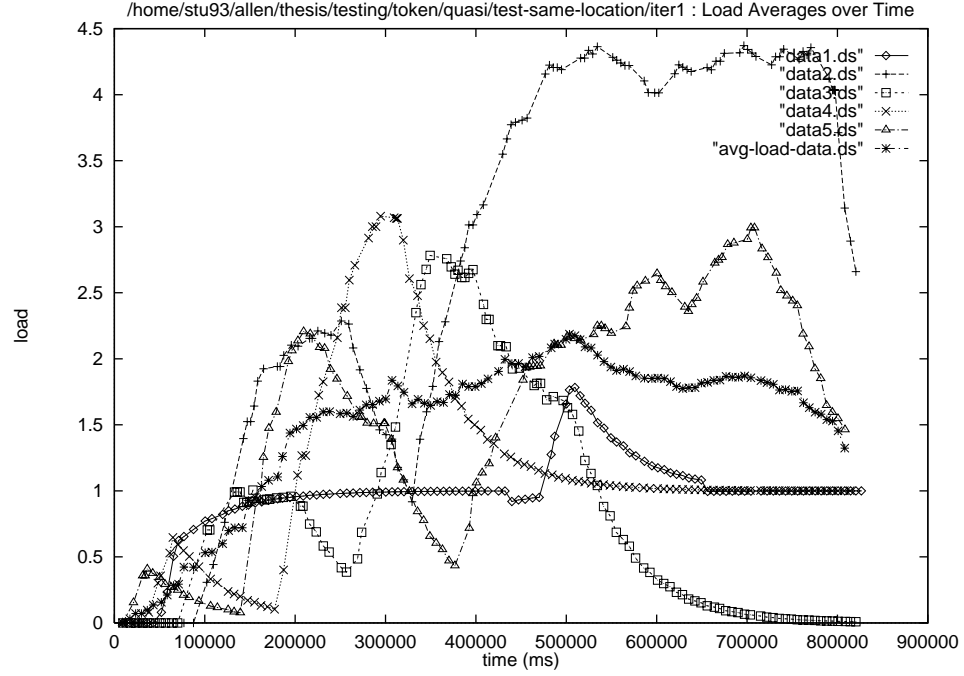


Figure A.44: Token-based Algorithm – Quasi-simulated environment – Test Case : Test Same Creation Location – Iteration 1 – Load Averages over Time

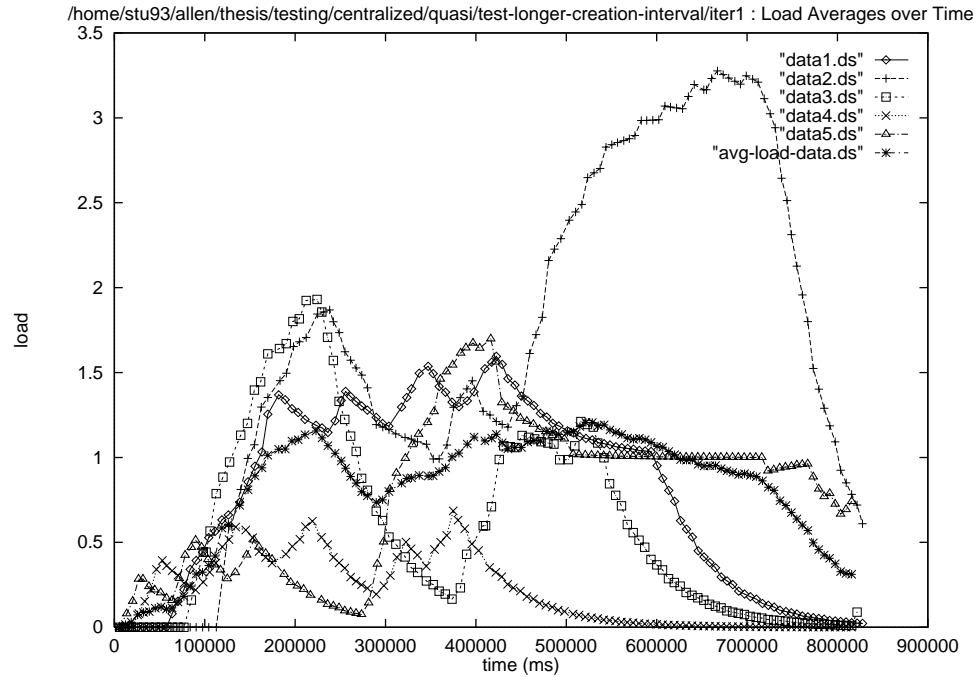


Figure A.45: Centralized Algorithm – Quasi-simulated environment – Test Case : Longer Creation Interval – Iteration 1 – Load Averages over Time

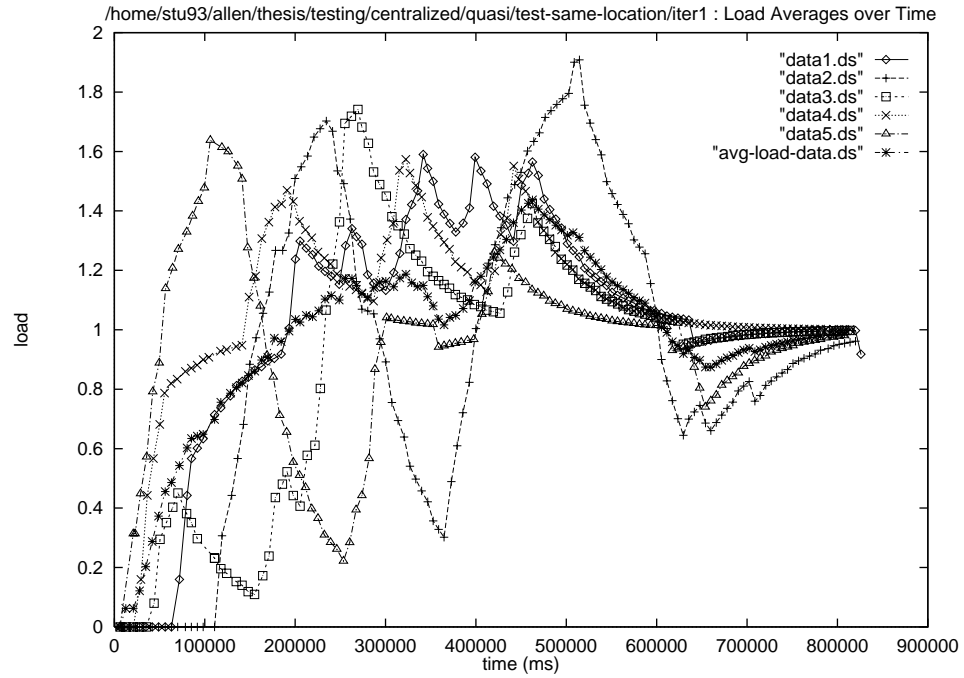


Figure A.46: Centralized Algorithm – Quasi-simulated environment – Test Case : Test Same
Creation Location – Iteration 1 – Load Averages over Time

Bibliography

- [CJK95] H. Cejtin, S. Jagannathan, and R. Kelsey. Higher-order distributed objects. *ACM Transactions on Programming Languages and Systems*, September 1995.
- [CK87] Thomas L. Casavant and Jon G. Kuhl. Analysis of three dynamic distributed load-balancing strategies with varying global information requirements. *7th International Conference on Distributed Computing*, pages 185–192, 1987.
- [ELZ86] D.L. Eager, E.D. Lazowska, and J. Zahorjan. Adaptive load sharing in homogeneous distributed systems. *IEEE Transactions on Software Engineering*, pages 662–675, May 1986.
- [Fuc95] M. Fuchs. Escaping the event loop: an alternative control structure for multi-threaded guis. *Engineering the Human Computer Interface*, pages 12–22, 1995.
- [FYN88] Donald Ferguson, Yechiam Yemini, and Christos Nikolaou. Microeconomic algorithms for load balancing in distributed computer systems. *1988 IEEE 8th International Conference on Distributed Computing Systems*, pages 491–499, 1988.
- [HJ87] Anna Hac and Xiaowei Jin. Dynamic load balancing in a distributed system using a decentralized algorithm. *7th International Conference on Distributed Computing*, 1987.
- [HL96] Babak Hamidzadeh and David J. Lilja. Dynamic scheduling strategies for shared-memory multiprocessors. *16th International Conference on Distributed Computing Systems*, pages 208–215, 1996.
- [HS97] Chao-Ju Hou and Kang G. Shin. Implementation of decentralized load sharing in networked workstations using the condor package. *Journal of Parallel and Distributed Computing*, pages 173–183, February 1997.
- [KL88] Phillipp Krueger and Miron Livny. A comparison of preemptive and non-preemptive load distributing. *1988 IEEE 8th Int'l Conference on Distributed Computing Systems*, pages 123–130, 1988.
- [LLM88] Michael J. Litzkow, Miron Livny, and Matt W. Mutka. Condor - a hunter of idle workstations. *1988 IEEE 8th Int'l Conference on Distributed Computing Systems*, pages 104–111, 1988.
- [ML87] M.W. Mutka and M. Livny. Scheduling remote processor capacity in a workstation-processor bank network. *Proceedings of the Seventh International Conference on Distributed Computing Systems*, pages 2–9, 1987.
- [PPTT] Dave Presotto, Rob Pike, Ken Thompson, and Howard Trickey. Plan 9, a distributed system. *ftp://research.att.com:dist/plan9doc*.
- [PTS88] Spiridon Pulidas, Don Towsley, and John A. Stankovic. Imbedding gradient estimators in load balancing algorithms. *1988 IEEE 8th International Conference on Distributed Computing Systems*, pages 482–489, 1988.

- [Stu88] M. Stumm. The design and implementation of a decentralized scheduling facility for a workstation cluster. *Proceedings of the 2nd IEEE Conference on Computer Workstations*, pages 12–22, March 1988.
- [Tan95] Andrew S. Tanenbaum. *Distributed Operating Systems*. Prentice Hall, Englewood Cliffs, NJ, 1995.
- [TL88] Marvin M. Theimer and Keith A. Lantz. Finding idle machines in a workstation-based distributed system. *1988 IEEE 8th International Conference on Distributed Computing Systems*, pages 112–122, 1988.
- [WT80] L.D. Wittie and A.M. Van Tilborg. Micros, a distributed operating system for micronet, a reconfigurable network computer. *IEEE Transactions on Computing*, pages 1133–1144, 1980.

Biography

Joshua S. Allen was born in Nashville, TN, USA on March 6, 1975. He attended Greenbrier Elementary, Middle School, and High School in Greenbrier, TN from 1980 through 1993. In high school, Joshua was very active in Show Choir, Band, Yearbook, and Student Government. He graduated valedictorian of his high school class.

Joshua was an undergraduate at Tulane University in New Orleans, LA, from 1993 through 1997, when he graduated with a Bachelors Degree in Computer Science. While still an undergraduate, Joshua started working on his Masters requirements in Computer Science. He plans to graduate in May 1998, and start work in August with IBM in Research Triangle Park, NC.