# Achieving Performance Objectives for Database Workloads

by

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A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Mathematics
in
Computer Science

Waterloo, Ontario, Canada, 2010

# AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

# Abstract

In this thesis, our goal is to achieve customer-specified performance objectives for workloads in a database management system (DBMS). Competing workloads in current DBMSs have detrimental effects on performance. Differentiated levels of service become important to ensure that critical work takes priority.

We design a feedback-based admission differentiation framework, which consists of three components: workload classifier, workload monitor and adaptive admission controller. The adaptive admission controller uses the workload management capabilities of IBM DB2's Workload Manager (WLM) to achieve the performance objectives of the most important workload by applying admission control on the rest of the work, which is less important and may or may not have performance objectives. The controller uses a feedback-based technique to automatically adjust the admission control on the less important work to achieve performance objectives for the important workload. The adaptive admission controller is implemented on an instance of DB2 to the test the effectiveness of the controller.

# Acknowledgements

First, I would like to thank my supervisor Professor Kenneth Salem for his immense patience and helpful advice. His continuous support not only helped me complete this thesis, but also helped me stay optimistic through the low phases of life, when the progress was extremely slow. I also owe many thanks to Keith McDonald at IBM Canada for his expert guidance with DB2 Workload Manager (WLM) and his Database Workload Generator (DWG).

I would like to thank my readers Professor Ihab Ilyas and Professor Tim Brecht for helping me significantly improve the quality of this thesis.

I am grateful to Paul Bird and Calisto Zuzarte for giving me an opportunity to spend a summer at IBM Toronto Lab which not only led to this thesis work, but was also great fun. I would like to thank Patrick Tayao, David Needs, Lee Johnson and Ahsan Khan for providing immediate support during my initial frustrations with DB2 server issues and system issues.

I thank IBM Canada and Ontario Graduate Scholarship program for providing funding for this research.

Finally, I would like to thank my family for supporting me, even if my decisions didn't always make sense to them.

# Dedication

This is dedicated to my sister, Alekhya.

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# Chapter 1
# Introduction

Database management systems (DBMS) must accommodate a variety of workloads, which come in from different sources, and which may have different service-level objectives. Service-level objectives may be time-based, such as a goal to keep the throughput or the response time of a workload to be below a certain threshold, or may be hard to quantify, such as a goal to keep the users of a database happy and to prevent any aberrant database activity from hampering their day-to-day work [1]. Time-based objectives are a standard representation of the performance requirements of the workloads and hence, are most commonly known as performance objectives. In essence, a performance objective of a workload reflects the workload's desired resource requirements.

In a resource constrained environment, achieving the performance objectives of all of the workloads may be impossible. Differentiated levels of service become necessary. Our objective in this thesis is to design a mechanism which ensures that the performance objectives for the most important workload are met, while handling the rest of the work, which is less important and may or may not have performance objectives, at the best level possible. For example, if there is a large amount of work from a less important application taking up most of the resources in a DBMS, deteriorating the performance of a workload from an important application, we can throttle the less important application just enough to achieve the performance objective of the important workload. The idea is not to waste scarce system resources on less important work in a DBMS. From here on in this thesis, we call the most important workload the *primary workload* and the other, less important workload the *secondary workload*.

Admission control is a popular technique used for load control in DBMSs. The load of a workload in a system can be regulated by controlling the workload's admission level, defined as the number of queries from that workload that are allowed to execute at any given time. Those queries that are not admitted because the workload's admission level has been reached are placed in a waiting queue so that they can be processed at a later time. Therefore, we essentially work on service differentiation through admission control, which we will call *admission differentiation* from here on, to achieve performance objectives. In this thesis, we present an architectural framework that applies admission control on the secondary workloads so that the primary workload can achieve its performance

objective. The framework not only uses admission differentiation to achieve performance objectives for a primary workload, but also ensures best-effort service for the secondary workloads.

Admission control requires accurate calculation of the admission level for the secondary workloads. If the admission level is too low, we end up delaying a lot of queries, resulting in an underutilized system. If the admission level is too high, we end up admitting too many queries, which might result in unfulfilled performance objectives. Therefore, we need an analytical method as framework's decisional underpinning.

Feedback-based techniques can provide an analytical foundation for achieving a performance objective. They use the current performance of the primary workload as feedback to adjust the amount of admission control on the secondary workloads. The amount by which the admission control level should be adjusted is calculated by using control theory [2]. It enables our framework to not only converge onto a performance objective value efficiently but also adapt to unpredictable workload changes in the system. Hence, we call the framework *feedback-based admission differentiation*.

This thesis makes two principal contributions:

- An architectural framework for feedback-based admission differentiation (Chapter 3). The framework achieves performance objectives of a primary workload on an instance of IBM DB2. The framework includes a feedback-based control loop that adds to the existing workload management capabilities in DB2's Workload Manager [1]. In the feed-back control loop, the current performance of the primary workload is measured and compared to its objective, based on which the amount of control on the secondary workload is manipulated at regular intervals.
- An empirical evaluation of the admission controller mechanism (Chapter 4). We test the mechanism in different scenarios, in which workloads and performance objectives are varied.

The rest of the thesis is structured as follows. Chapter 2 presents related work on admission control and how it has been used to achieve various performance objectives. Chapter 3 presents an architectural framework for feedback-based admission differentiation. We discuss the design and implementation of the key functional components involved in the framework that work together to achieve performance objectives for the primary workload by applying admission control on the secondary workload. Chapter 4 presents a performance analysis of the mechanism. The thesis

concludes with an explanation of the lessons learned, suggestions for enhancements and future research in this line of work for database management systems.

# Chapter 2
# Relevant Work

Current research in workload management concentrates on workload performance management. Various methods for manipulating the performance of the workloads have been proposed. A query's life in a workload gives us three areas of scope for controlling performance of a workload. The first opportunity is to decide whether a new query coming into the system is to be allowed to execute immediately or not. Those that are not executed immediately might be delayed (queued) or rejected. The second opportunity is to make scheduling decisions for the rejected queries. The third opportunity is to control the execution of running queries [3]. These three opportunities have led to a significant amount of work, resulting in three important types of resource control in workload management: admission control [4-14], query scheduling [8, 9, 13, 15-17] and execution control [18-21]. Since we use admission control as the resource control technique, we focus on the admission control research.

Admission control has been traditionally used for OLTP workloads to prevent potential problem queries from overloading the system. Admission control works by adjusting the *multi-programming level* (MPL), which is the maximum number of queries that are permitted to run concurrently.

Unfortunately, choosing an MPL is not an easy task. If the MPL is set too high then it leads to system overloading and if the MPL is set too low then it leads to system underutilization. Moreover, with database systems having to operate in changing workload conditions, the MPL should be adaptive. Therefore, it may be difficult for a human system administrator to tune the MPL manually. A significant body of work exists on admission control in the form of various feedback-based techniques to tune the MPL [4-14].

In the rest of this chapter, we present related work on admission control. In Section 2.1, we present the work in which admission control was used to control the load of all the workloads running on a system. They work on achieving global performance objectives. In Section 2.2, we present the work in which admission control has been used to achieve per-class performance objectives.

## 2.1 Load Control

Most of the early work on feedback-based techniques in applying admission control has focused on load control. These techniques aim at achieving an optimal MPL, which is high enough to maximize the throughput of the workload in the system and low enough to avoid overloading and performance degradation.

Monkeberg et al [4], Carey et al [5] and Heiss et al [6] focus on interactive transactional workloads. Moenkeberg et al [4] measure a performance metric called *conflict ratio*, which is the ratio of the number of locks held by all transactions to the number of locks held by active transactions. If the ratio exceeds a critical threshold of 1.3, found experimentally, the admission of new transactions is suspended, letting them queue. Otherwise one or more transactions waiting in the queue are admitted. Similarly, Carey et al [5] measure the *ratio of queued (blocked) transactions to running transactions*. If the ratio exceeds a threshold of 0.5, the admission of new transactions is suspended. Otherwise, one or more transactions are admitted. The work done by Moenkeberg et al [4] and Carey et al [5] uses static thresholds obtained through experiments to determine the amount of admission control to be applied. These thresholds may be specific to the test system used to conduct the experiments.

Unlike Moenkeberg et al and Carey et al, Heiss et al [6] use a more general approach to calculating the MPL in the system. They use two heuristic algorithms: incremental steps (IS) and parabolic approximation (PA). In the IS algorithm, they start with an arbitrary value for the MPL and then they increase the MPL by 1 at regular time intervals and measure transaction throughput. If the throughput has increased, then they continue to increase the MPL, or if the throughput has decreased, then they decrease the MPL at regular time intervals until the throughput starts to decrease again. In the PA algorithm, they use a parabolic function to determine the new MPL. The parabolic function approximates the performance in the system using the recent measurements of the performance for different MPL values. The maximum of the parabolic function is used as the new MPL. Their algorithm is restricted to parabolic performance functions and therefore the algorithm cannot be used with performance metrics that do not follow parabolic functions such as query latencies or response times which are often used to define service level objectives for workloads in current DBMSs. Their goal is to maximize throughput in the system and hence, find the highest possible MPL for the whole system that would prevent overloading. In contrast, our goal is to achieve performance objectives for a primary workload and hence, find the best possible MPL on the secondary workload. We use fundamentals from control theory for calculating the MPL on the secondary workload.

Kang et al [7] also use admission control to control the load. They pre-determine the CPU utilization of a query and admit it only if its CPU utilization requirement is available in the system to service it. Similarly, Elnikety et al [8] also use admission control to provide overload protection for web servers by rejecting requests which would overload the server and placing them in a queue. Their goal is to see to it that the current CPU utilization does not exceed the system's capacity. In order to admit a query, they pre-estimate the CPU utilization of the query. They add the estimate to the current CPU utilization, which is also an aggregated estimate of the CPU utilizations of all the previously admitted queries that are running in the system. If the sum is less than the system capacity, then query is admitted. Therefore, effectively, they use estimates to admit a query. In contrast, our controller uses the primary workload's current, actual performance to understand the effect of load caused by the secondary workload. Based on this feedback, the controller controls the CPU utilization of the secondary workload by controlling the secondary workload's MPL, which determines whether the workload's future, incoming queries can be admitted or not.

Schroeder [9] uses a combination of queuing theoretic models and feedback-based control to determine the optimal MPL for the server. Her approach takes as inputs (from the DBA) the maximum allowable thresholds for drop in throughput (from the highest throughput in the system) and increase in response time (from the lowest response time in the system) and determines the lowest optimal MPL. The queuing theoretic models are used to find a close-to-optimal MPL and then, a feedback-based controller compares the current throughput and the current response time with their respective thresholds. Based on these comparisons, the controller makes conservative adjustments to the determined MPL. Similarly, Kang et al [10] also implement admission control by controlling the MPL to control data contention. They measure the system's data contention in the form of a *data contention ratio*, which is the ratio of the number of locks held by all transactions (blocked and active) to the number of locks held by active transactions. Their goal is to achieve a user-specified, desired threshold for the data contention ratio. Based on the measured value of the data contention ratio and the desired threshold, they use control theory to determine the amount by which the MPL is to be tuned. Similarly, we also use fundamentals from control theory to determine the amount by which the MPL is to be tuned. However, Kang, Sin and Shin concentrate only on data contention due to locking involved between queries running in the system. Our controller approach differs in that our framework works with workloads for which CPU contention is the problem. In addition, Kang et al cancel admitted transactions that are blocked, waiting for locks, to alter the MPL in the database server, but we do not cancel any admitted transactions.

As explained in the previous chapter, unlike all of the above work, we do not apply admission control globally throughout the system to prevent overloads and we do not achieve global performance objectives. Instead, we apply admission control on the secondary workloads alone to regulate the CPU load caused by them just enough to achieve performance objectives for the primary workload.

## 2.2 Achieving Per-Class Performance Objectives

There exists a fair amount of work on using admission control to achieve performance objectives for individual workloads. The workloads are categorized into workload classes and each class is monitored and controlled to achieve its performance objective.

Brown et al [11] were among the first to work on achieving performance objectives for workload classes in a DBMS. They introduced an algorithm called M & M that uses memory allocation and MPL to achieve response time objectives for workload classes. They classify queries into workload classes according to their performance objectives. Then, they use a set of heuristics to determine the MPL and the memory allocation for each workload class. The heuristics filter the search space of possible solutions of combinations of the MPL and the memory allocation for a workload. These heuristics underappreciate the interdependencies among the workloads. Workloads are dependent on one another because they compete for shared resources. For example, if the MPL of a workload is increased, this improves the performance of the workload, but it may result in increased response time for the other workloads. Brown et al solve this dependency problem by incorporating performance feedback along with their heuristics. They measure the response time of a class regularly after a certain number of query completions and compare it to the objective. Based on the results of the comparison, they tweak the MPL and the memory allocation settings. Our work is different from M & M, because we don't try to logically partition the available resources between various workload classes to achieve their performance objectives by performing direct resource allocation. We try to achieve performance objectives in an overloaded environment by sharing the available resources among the workload classes. Our admission differentiation uses the interdependence of the workload classes by using admission control on the secondary workloads to affect the performance of the primary workload.

The M&M is devoid of any knowledge regarding the business importance of the workloads. Pang et al [12] integrate the importance of the workloads into their MPL and memory settings. Pang et al classify queries into workload classes based on their importance. Like M&M, the algorithm of Pang et al achieve the response time objective of a class by measuring the response time of the class regularly after a certain number of query completions and comparing it to the objective. The MPL is based on this comparison. The MPL is calculated by using a statistical projection called the miss ratio, which is the proportion of queries that fail to complete by their deadlines. If the statistical projection fails, they use resource-utilization heuristics.

Apart from using admission control through MPL, Brown et al [11] and Pang et al [12] use direct resource allocation by allocating memory for each workload class in order to achieve the class's performance objective. The advantage of using direct resource allocation is that a finer granularity can be achieved in controlling the performance of a workload. However, a disadvantage of this approach is that it requires changes to database internals and working at a level that requires operating system support. Our approach is different in that we design and implement an admission control mechanism that works at a level external to the database engine. The advantage of this approach is that it does not depend on changes to the database internals, making portability easier, or knowledge of the resource utilization of the workload, making implementation easier. Brown et al and Pang et al also test their approach in a simulated environment without experimental validation on a DBMS.

### 2.2.1 Admission Differentiation

In current resource-constrained systems, if all workload classes are processed with the same level of urgency, then the workloads can compete with each other for shared resources. This can be detrimental on the performance of the system as a whole. Achieving performance objectives of all of the workload classes may not be possible. One workload class has to be favoured over another workload class. Therefore, the importance of the workload classes needs to be considered while achieving their performance objectives.

The following is work done on the use of admission control to provide service differentiation in web servers. Bhatti et al [13] perform a part of their service differentiation by performing admission control on lower priority requests. Such requests are rejected when the number of higher priority requests waiting in the execution queue exceeds a certain threshold, which is determined through

experimentation. Rejection is accomplished by closing the connection of the request. Like Bhatti et al, we also apply admission control on secondary workloads to prevent our primary workload's performance from being affected due to overload in database management systems.

Similarly, Abdelzaher et al [14] also combine service differentiation with admission control. They achieve a performance objective, *capacity utilization*, for a high-priority workload class by applying admission control on a lower priority workload class to control the MPL. The lower priority requests that will exceed the MPL are rejected. They use a combination of proportional and integral control to determine the MPL by monitoring the current utilization and comparing it with the objective. Our work in this thesis applies admission differentiation in the same way as Abdelzaher et al to workloads in database management systems. We achieve response time objectives for the primary workload through admission control in the form of controlling the MPL of the secondary workloads. We also use fundamentals from control theory in our decision logic to determine the amount by which the MPL has to be changed. However, their components that make up the controller require changes to the server internals for implementation. Unlike Abdelzaher et al, we work outside the database engine and therefore we do not touch the database internals.

## 2.3 Summary

In summary, there are three take away concepts from this chapter.

1. MPL control: All of the above work has implemented admission control by controlling the MPL. Many kinds of performance objectives can be achieved by controlling the MPL. Our algorithm also controls the MPL of the secondary workloads to achieve the performance objectives of the primary workload.

2. Feedback-based control: All of the above work, except Kang et al [7] and Elnikety et al [8], use monitoring as a part of their approach for admission control. They integrate monitored information into decision making for calculation of the MPL value. We do the same by monitoring the performance of the primary workload to determine the admission control to be applied to the secondary workloads.

3. Decision logic: Most of the work done on admission control, either to provide overload protection or to achieve a performance objective, uses predefined heuristics and simple mathematical approaches in calculating the amount of admission control to be applied. Like

Kang et al [10] and Abdelzaher et al [14], we use fundamentals from control theory in our decision making because they have been popularly used for working in dynamic scenarios.

# Chapter 3
# Design and Implementation

In this chapter, we present the design of an architectural framework for feedback-based admission differentiation. Our high-level design goal is to adaptively achieve performance objectives for the primary workload. If there are changes in the workloads or the performance objectives, the framework's components should work together to dynamically respond to changes without the intervention of the database administrator and achieve performance objectives for the primary workload. For implementing the framework, we use IBM DB2 as our database management system. Before presenting the framework and its components, we present our performance objective specification.

## 3.1 Performance Objective Metric

The most commonly used performance metrics for performance objectives are throughput [6, 9] and response time [9, 11, 12]. Throughput is usually used for batch workloads. Batch workloads aim at maximizing their utilization of the processor so that the workloads finish within a specified time interval, known as the batch window. These workloads focus on executing as many queries as possible and therefore, it suffices to focus on the number of transactions completed. Response time objectives are commonly used for transactional workloads. For our implementation, we use CPU-bound transactional workloads and therefore, we try to achieve response time objectives.

Response time of a query is best understood as the time elapsed from the submission of a query to its completion of execution. Figure 1 shows the life of a CPU-bound query in the system. In our scenario of admission control, response time $R$ of a query includes time spent waiting in a queue outside the database engine (if admission control is applied), queuing time $T_Q$, and the time spent executing inside the database engine, execution time $T_E$.

$$R = T_Q + T_E$$

Execution time $T_E$ of a query includes the time spent receiving CPU resources, CPU service time $T_S$, and the time spent waiting for CPU resources, CPU wait time $T_w$.

$$T_E = T_S + T_w$$

Therefore,

$$R = T_Q + T_S + T_w$$

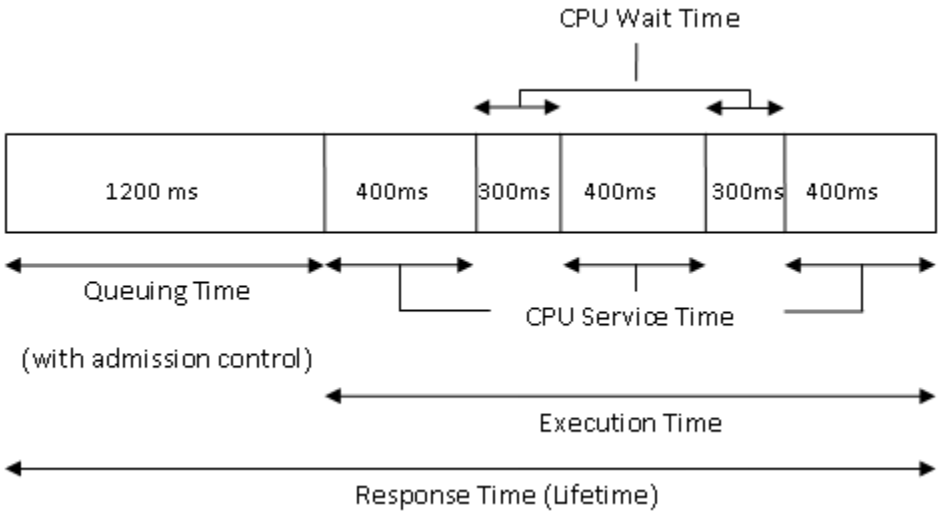



**Figure 1: CPU-bound Query's Life**

In order to regulate the response time of a workload towards the workload's performance objective, the queuing time or the CPU service time or the CPU wait time of the queries of the workload should be controlled. We do not apply admission control on the primary workload and therefore, there is no queuing time $T_Q$ for the primary workload. Service time $T_S$ is the inherent nature of a query and therefore, cannot be changed. CPU wait time $T_w$ is mainly dependent on the CPU resource contention. Hence, the focus of our framework narrows down to controlling the CPU wait time $T_w$ of the primary workload by controlling the CPU contention in the system, which is done by applying admission control on the secondary workload.

**Response Time Objective Specification**

In this thesis, we aim at achieving a response time objective for the primary workload. For example, average response time of the workload should be 1000 ms.

## 3.2 Feedback-based Admission Differentiation Architectural Framework

In this section, we present the components required to perform feedback-based admission differentiation and discuss the design and implementation of each component involved.

### 3.2.1 Framework Components

Figure 2 shows the architectural framework for feedback-based admission differentiation. The framework consists of three components: workload classifier, workload monitor and adaptive admission controller. The workload classifier identifies the incoming queries and groups them into classes. The purpose of workload classification is to define workloads and assign each incoming query to a workload, providing a finer granularity for the workload monitor component and the controller. The workload monitor monitors the performance of all the workload classes running in DB2. The adaptive admission controller calculates and implements admission control. The controller consists of two sub-components: *advisor* and *effector*.

The advisor is given the response time objective. It measures the response time of the primary workload regularly through the workload monitor. Using this information, it determines the amount of admission control to be applied to the secondary workloads. The effector implements the admission control.

DB2 provides workload management through its tool called Workload Manager (WLM) [21], which is the priority and resource manager of DB2. WLM provides comprehensive features for classifying the incoming queries, monitoring and controlling the executing workloads within DB2. We use WLM's functionalities to implement all of the components of our framework.

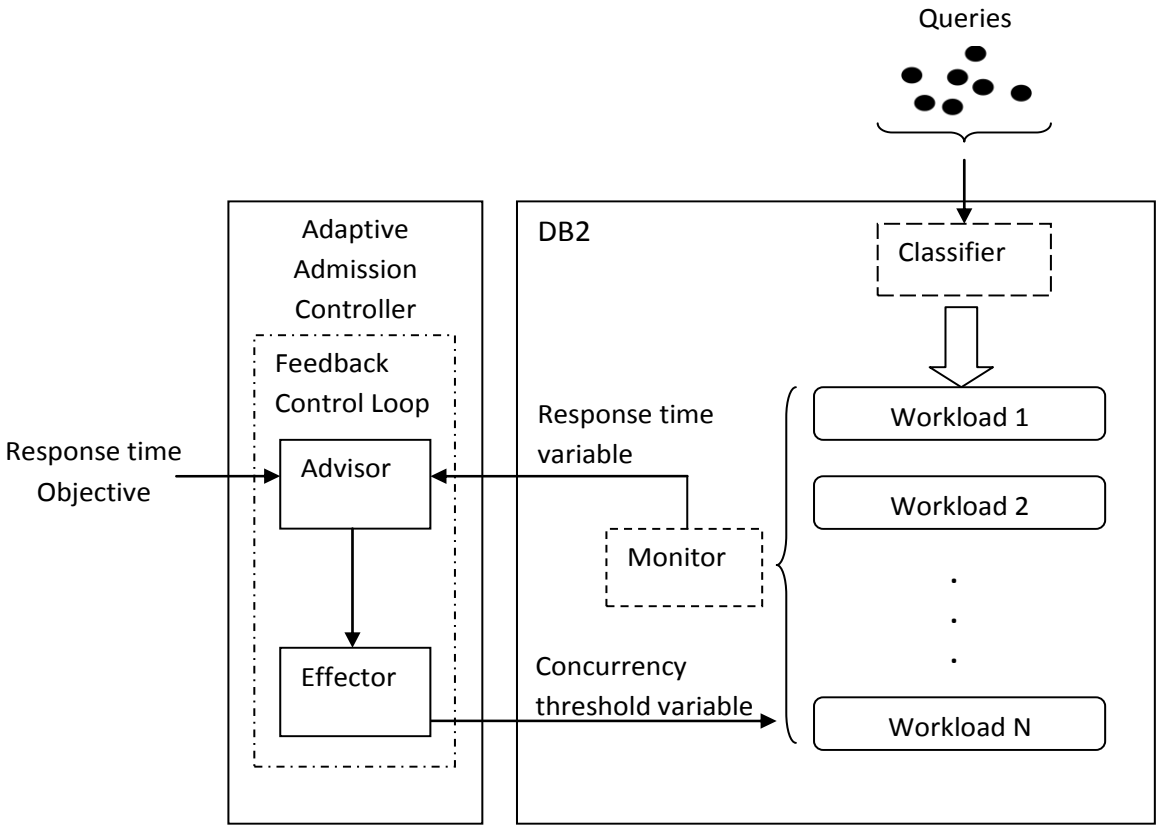



**Figure 2 Feedback-based Admission Differentiation Framework**

### 3.2.1.1 Workload Classifier Component

The first step in our framework is workload classification. Workload classification is done by identifying the incoming queries and partitioning them into workload classes. Partitioning the incoming queries into workload classes not only increases the manageability of the workloads but also allows the workload monitor to collect performance information on a per-workload basis and allows the admission controller to define distinct control strategies for different workload classes.

Previous work on achieving performance objectives for workloads implemented workload classification based on workload type [11] or based on business importance [12, 13, 14]. In DB2, WLM serves as the triage point through which all of the queries coming into DB2 have to pass. The first step in WLM is workload classification. WLM identifies an incoming query based on the source or the type of the query. After identifying an incoming query, WLM maps the query to a workload

class and subsequently, maps all the other queries coming in from the same source or of the same type to the same workload class.

In the implementation of our adaptive admission controller on DB2, for simplicity, we assume that there are only two workload classes, primary and secondary. The workload classifier has to be configured to identify the primary workload queries and group them into a primary workload class and group all other incoming queries into a secondary workload class. Hence, each workload should have its own individual workload class so that we can monitor each workload class individually and control each workload class uniquely.

#### 3.2.1.2 Workload Monitor Component

Workload monitor collects the performance information of the workloads. DB2's WLM provides various means of capturing performance information about individual workloads running on the system. There are table functions that provide access to real-time information and event monitors to capture detailed query information and aggregate information for historical analysis [21]. Statistics from an event monitor can be read by resetting the statistics. Statistics can be reset by using a stored procedure called WLM_COLLECT_STATS(), which sends the statistics to a set of tables and histograms. The statistics can then be viewed by querying the statistics tables and viewing the histograms. In contrast, table functions can be used to obtain point-in-time execution information without having to reset statistics.

In the implementation of our adaptive admission controller, we focus on the response time information of the primary workload. In order to understand whether the primary workload is meeting its response time objective or not, we need to use an event monitor to capture response times aggregated over a single control interval, after which the statistics need to be reset so that the next control interval can be monitored. We use the event monitor DB2STATISTICS to collect aggregate execution information. For obtaining response time information, WLM provides lifetime average and execution time average in milliseconds. Lifetime average is the sum of queuing time average (due to admission control by WLM) and execution time average. Execution time average is the sum of CPU service time and CPU wait time. Therefore, in our implementation, if we want to measure the response time average of the primary workload, we use execution time average and if we want to

measure the response time average of the secondary workload, we use lifetime average because it includes queuing time due to admission control as well.

The response time average of the primary workload is read by querying for the execution time average COORD_ACT_EXEC_TIME_AVG and the response time average of the secondary workload is read by querying for the life time average COORD_ACT_LIFETIME_AVG from the statistics table SCSTATS_DB2STATISTICS, where the event monitor's aggregate statistics of all the workloads are written to.

#### 3.2.1.3 Adaptive Admission Controller

The control component is the final and the main part of our framework. Our adaptive admission controller implements admission control on the secondary workload in order to achieve a performance objective for the primary workload. With our design objective being that the framework should be adaptive, our controller uses a feedback control loop that manipulates the CPU load caused by the secondary workload. The feedback control loop controls the secondary workload's admission configuration parameter that changes the workload's MPL by an amount that is just enough to ensure that the primary workload is achieving its performance objective. This ensures that the secondary workload receives the best service possible, given the primary workload's objective.

Before we present the variables and the feedback control loop involved in the controller, we define the admission configuration parameter.

##### 3.2.1.3.1 Admission Configuration Parameter

An admission configuration parameter is a dynamic system parameter that sets the MPL for an individual workload. DB2's WLM offers, for each workload, a concurrency threshold CONCURRENCTDBCOORDACTIVITIES that specifies the number of workload queries that can run concurrently. In addition, the concurrency threshold is a queuing threshold, which means that the queries that are not admitted are placed in a first come first serve (FCFS) queue. We can either choose to have no queuing or limit the queue length or have an unbounded queue length.

For our implementation of the controller, we use the concurrency threshold with an unbounded queue length, since we choose to not reject any incoming secondary workload queries.

3.2.1.3.2 Feedback Control Loop

The controller invokes a feedback control loop after every control interval. The feedback control loop deals with three variables when the feedback control loop is invoked the *i*th time:

1. *Response time variable* $R(i)$ is the measured response time average of the primary workload during the control interval that just ended. The controller aims at making the response time variable match the response time objective.
2. *Response time objective* $R_S$ is the given response time target for the primary workload. The difference between the response time objective and the response time variable is error $E(i) = R_S - R(i)$.
3. *Concurrency threshold (or controller output) variable* $C(i)$ is the controller output value calculated by the feedback control loop for the admission configuration parameter. This is the concurrency threshold of the secondary workload that will be used for the next control interval.

The feedback control loop takes the following actions:

1. The advisor obtains the current response time $R(i)$ of the primary workload from the workload monitor and compares it to the response time objective $R_S$ and calculates the error $E(i)$. The control logic is then used to calculate a new value for the concurrency threshold variable $C(i)$.
2. The effector sets the admission configuration parameter to the new value of concurrency threshold variable $C(i)$.

Further in this section, we discuss the inputs and the components of the feedback control loop.

**Control Interval *I***

Control interval defines the window at the end of which the feedback control loop is invoked. The control interval can be a time interval [6] or it can be based on a number of queries completed [11, 12].

The length of control interval should be chosen carefully. If the control interval is too short, then the controller output *C(i)* may oscillate because there will be significant variance in the measured

values of the response time variable $R(i)$. The variance is due to low number of queries in the control interval over which the response time is averaged. If there are more queries, then the variance can be reduced. If the control interval is too long, then the controller will take too long to make the response time of the primary workload converge onto the given response time objective. The controller will adapt to the changes in the workload or changes in the response time objective slowly. Therefore, the control interval $I$ should be chosen carefully. Chapter 4 further discusses how $I$ should be chosen and how $I$ affects the performance of the controller.

In our implementation of the controller, we use a control interval based on the number of primary workload queries completed. The controller invokes the feedback control loop after a minimum number, $q$, of primary workload queries are completed. In order to obtain information about the number of primary workload queries executed, we query point-in-time information from a table function after every polling interval $t$, which is a time interval, to check whether $q$ queries have been completed or not. Therefore, the length of each control interval is a multiple of the polling interval $t$ and it may vary. The polling interval $t$ should be smaller than the time taken by $q$ queries to be completed and ideally, a factor of the control interval I. If $t$ is too small, then the controller queries the table function many times before $q$ queries have been completed which is unnecessary. If $t$ is too big, then the controller may query the table function much after $q$ queries have been completed.

We query point-in-time information for COORD_ACT_COMPLETED_TOTAL, the number of queries completed since the last reset, from a table function WLM_GET_SERVICE_SUBCLASS_STATS.

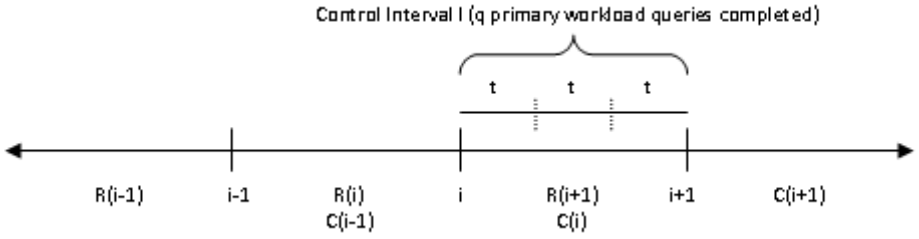



**Figure 3: Feedback control loop timeline and control interval I**

**Control Theory Logic**

The feedback control loop in this framework is designed to use fundamentals from feedback control theory [2] as its decision logic. Feedback control theory has been applied extensively in mechanical systems [2]. Recently, it has started to become widely used a mathematical foundation for decision making in control plans in computing [2, 11, 15].

In feedback-based control, depending on how the feedback information is used by the controller, different levels of performance can be achieved. The simplest form of feedback-based control is proportional control. If we use proportional control, the concurrency threshold variable $C(i)$ is proportional to the error; $C(i) = K_P * E(i)$ where $K_P$ is a tunable constant referred to as proportional gain [2]. The effective result is to immediately react to the instantaneous error $E(i)$ to correct it. Therefore, the disadvantage of proportional control is that it can react to short, transient disturbances by immediately trying to correct it.

In contrast to proportional control, another form of feedback-based control is integral control. If we use integral control, the *change* in the concurrency threshold variable $C(i)$ is governed by the error; $C(i) = C(i-1) + K_I * E(i)$, where $K_I$ is a tunable constant [2]. The effective result is to accumulate all the errors over time to determine the concurrency threshold.

$$C(1) = C(0) + K_I * E(1)$$

$$C(2) = C(1) + K_I * E(2)$$

$$\vdots$$

$$C(i) = C(0) + K_I * E(1) + K_I * E(2) + \cdots + K_I * E(i)$$

$$C(i) = C(0) + K_I \sum_{j=1}^{i} E(j)$$

Since integral control acts upon past errors, it tries to respond more to sustained change in response time rather than short, transient disturbances in response time. Therefore, with databases workload being prone to transient disturbances, we use integral control as our logic in the implementation of the controller.

In our implementation of the controller, we choose to not completely shut out the secondary workload queries from running. Therefore, we use the following to determine the concurrency threshold so that we have at least one secondary workload query running in the system at all times.

$$C(i) = \max\{1,\ K_I \sum_{j=1}^{i} E(j)\}$$

The *integral constant* $K_I$ defines the sensitivity of the controller's output, i.e. the concurrency threshold, to the error. From the integral control equation,

$$C(i) = C(i-1) + K_I * E(i)$$

$$C(i) - C(i-1) = K_I * E(i)$$

$$K_I = \frac{C(i) - C(i-1)}{E(i)}$$

Therefore, $K_I$ is the amount by which the controller should manipulate the concurrency threshold for a unit error in the response time of the primary workload.

If $K_I$ value is too high, then the feedback control loop makes large changes to the concurrency threshold variable *C(i)* for a given error,. This can make the controller aggressive in responding to errors, resulting in performance problems of overshoot and oscillation. If $K_I$ value is too low, then it can result in making the feedback control loop too conservative in responding to errors in the response time of the primary workload. This results in making the controller less sensitive to changes in the system, such as changing workload. Hence, the value integral constant $K_I$ should be chosen carefully. It should be noted that $K_I$ is specific to the workloads and the system being used. Therefore, in our experiments presented in the next chapter, we choose $K_I$ experimentally, by trying different values for $K_I$ to see how the feedback control loop reacts and tune the value accordingly. In Chapter 4, we further discuss how controller constant $K_I$ affect the performance of the controller.

#### 3.2.1.3.3 Adaptive admission controller algorithm

Algorithm 1 shows how the adaptive admission controller works with the feedback control loop and all of the variables defined. The algorithm consists of three steps: sample, calculate and manipulate. These three functions constitute the feedback control loop described earlier in this section. The

sample step and calculate step make up the advisor sub-component and the manipulate step makes up the effector sub-component.

Input: Polling interval $t$, Minimum query count $q$, Response time objective $R_S$, Integral constant $K_I$

*// Initialize number of completed primary workload queries and accumulated error*

$n = 0$ and $E = 0$;

while *workloads run* do

  *// Ensuring a control interval of a minimum of q completed primary workload queries has lapsed*

  while $n < q$ do

    *// Waiting idle for t seconds before the number of completed primary workload queries is polled*

    wait $t$;

    *// Reading the number of completed primary workload queries since the last reset*

    $n \leftarrow$ Read COORD_ACT_COMPLETED_TOTAL from WLM_GET_SERVICE_SUBCLASS_STATS;

  end

  ***// Sample***

  *// Measure response time average of primary workload from the statistics table*

  $R \leftarrow$ Read execution time average from SCSTATS_DB2STATISTICS;

  ***// Calculate***

  *// Integrate error to implement integral control*

  $E = E + (R_S - R)$;

  *// Ensuring that at least one secondary workload query is allowed to run*

  $C = \max(1, K_I * E)$;

  ***// Manipulate***

  *// Half-up round C to integer*

  $C = round(C)$;

  // *Update concurrency threshold of secondary workload*

  Set CONCURRENTDBCOORDACTIVITIES to $C$;

  Reset statistics by calling WLM_COLLECT_STATS();

end

**Algorithm 1: Adaptive Admission Control**

Figure 4 shows a block diagram of the controller illustrating the feedback control loop and how all the variables are directed, as presented in Algorithm 1.

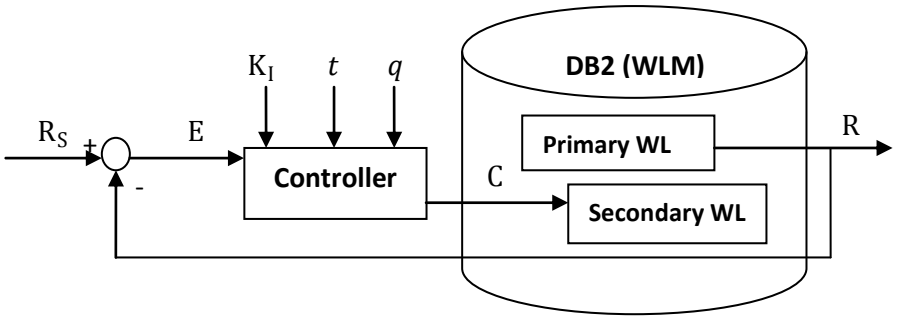



**Figure 4: Adaptive Admission Controller's block diagram**

## 3.3 Summary

In this chapter, we presented the design and implementation of a feedback-based admission differentiation framework. The framework consists of three components: a workload classifier, a workload monitor and an adaptive admission controller. The workload classifier is the starting point for the framework. It identifies and groups the incoming queries in the system into workload classes for finer monitoring and control. The workload monitor collects execution information for each workload individually. The adaptive admission controller uses DB2's workload management capabilities to dynamically change the concurrency threshold on the secondary workload to achieve response time objectives for the primary workload. In the implementation of the feedback control loop, the controller regularly uses WLM's statistics tables to read the average response time of the primary workload and compares it to the given response time objective to calculate the error. The controller integrates the instantaneous errors over time and uses the accumulated error to calculate the new admission control value. The controller implements the new admission control value by setting the concurrency threshold, provided by WLM, on the secondary workload.

# Chapter 4
# Experimental Evaluation

In this chapter, we evaluate the effectiveness of the admission controller in adaptively achieving response time average objectives. Specifically, we address the following questions in this chapter:

1. Does admission control on the secondary workload affect the response time for the primary workload?
2. Can the controller achieve response time objectives for a fixed workload?
3. Can the controller automatically adapt to changes in the response time objective of the primary workload?
4. Can the controller dynamically adapt to changing workload conditions in the system?
5. How do input parameters such as controller constant $K_I$ and control interval $I$ affect the performance of the controller?
6. Will the controller work for workloads consisting of small queries, coming in at a high arrival rate?

All the above questions are addressed experimentally. We designed a set of experiments to show effectiveness of the controller in various scenarios. In Section 4.4, we present the results of an experiment in which we test whether admission control is an effective choice for affecting the response time of the primary workload. Then, we move on to experiments with the controller.

In the controller experiments, we evaluate the controller's ability to achieve the response time objective with minimal overshoot, minimal oscillation and short convergence time. Each controller experiment is conducted by running the test workloads and the controller together for a period of 96 minutes on an instance of DB2. The controller is given the required response time objective $R_S$, controller constant $K_I$, control interval $I$ (shown as the minimum query count $q$) and polling interval $t$ as inputs.

In Section 4.5, we present the results of controller experiments in which we show the performance of the controller on stable workloads with a fixed response time objective. In Section 4.6, we present the results of controller experiments in which we test the controller in a scenario in which the

response time objective changes halfway through the experiment. In Section 4.7, we present the results of controller experiments in which we test the controller in a scenario in which the workload changes halfway through the experiment. In Section 4.8, we present the results of controller experiments in which we show how controller constant $K_I$ and control interval $I$ affect the performance of the controller. In Section 4.9, we present the results of experiments in which we examine the feasibility of using our controller's admission control on workloads consisting of small queries, coming in at a high arrival rate.

Before we address the questions related to the effectiveness of the controller, in Section 4.1, we present the experimental system configuration used in the experiments. In Section 4.2, we present the synthetic test workloads used in the experiments and in Section 4.3, we test the intensity of the workloads to ensure that they will be useful in the experiments for testing the effectiveness of the controller.

## 4.1 Experimental Test Bed

The database server machine used runs DB2 Version 9.5 on Linux kernel 2.6.5-7.283–smp (x86_64). The system consists of four 2.0 GHz 64-bit Dual Core AMD Opteron (tm) processors. Therefore, the system has 8 cores. However, the DB2 server's fixed term license allows a maximum processor utilization of 4 cores only. Hence, in our experiments, the DB2 database engine uses 4 CPU cores at any given time. The threading degree is 1 thread per core. The system has 8 GB of RAM.

## 4.2 Database Workload Generator and Test Workloads

The workloads used to test the controller were generated using a database workload generator called DWG. DWG is a Java program that generates read-only CPU bound workloads. DWG begins by spawning a number of threads, each of which obtains a database connection to the DB2 data server, and issues queries through the connections. DWG generates transactional workloads with random query service time ($T_S$) and query inter-arrival time ($T_A$). DWG allows the users to specify the distributions that the service times and the inter-arrival times should follow. DWG is also capable of generating multiple concurrent workloads, each with a distinct, user-specified query service and inter-arrival time distributions.

DWG defines and populates a set of tables against which its queries will be issued. A basic query that DWG generates is to count the number of rows in the result of a join of many tables in the database. In order to produce queries of various service times, variations of the basic query are produced by performing a variable number of unions of the query with itself, thereby varying the number of joins and the number of rows of the tables being queried.

DWG allows a user to choose from the following two types of distributions, according to which the service times and the inter-arrival times are sampled:

1. *Empirical distribution:* DWG allows the user to specify an arbitrary, discrete cumulative distribution function as a series of service time or inter-arrival time values and their corresponding probabilities that the query service time or the query inter-arrival time is less than or equal to the values. In our experiments, we use empirical distribution to simulate workloads with deterministic, or fixed, service times or inter-arrival times by specifying a probability of 1 for a fixed value to be sampled.
2. *Exponential distribution:* DWG can also generate exponentially distributed times with a user-specified mean value. We use exponential distribution to generate workloads with random, or variable, service times or inter-arrival times.

DWG also allows a user to specify a particular username for each workload so that DWG can simulate the workload as if it is coming into the system from the particular username's terminal. DWG makes database connections to the DB2 data server for the queries from each workload with the workload's specified username. Therefore, we specify different usernames for the primary workload and the secondary workload. We configure the workload classifier to identify primary workload queries coming in from the same user and map them to one workload class and all the other queries coming into the system from another user are considered secondary and mapped into another workload class.

We design our test workloads' service times and inter-arrival times in such a way that when both the workloads run together, they overload the system, creating our problem scenario. We use the following statistic to ensure high CPU utilization.

$$CPU\ utilization = \frac{mean\ service\ time}{mean\ inter\text{-}arrival\ time}$$

We choose the service times and the inter-arrival times of the workloads as shown in Table 1. The primary workload, $W_A$, has a service time of 1000 ms and inter-arrival time of 2000 ms. This will ensure that the primary workload will keep 0.5 CPUs busy. The secondary workload, $W_B$, has a service time of 1000 ms and inter-arrival time of 300 ms. This will ensure that the secondary workload will keep 3.33 CPUs busy. When both the workloads run together, they will keep, on average, 3.83 CPUs busy.

We use deterministic (empirical distribution) service times for both the workloads for simplicity in interpretation of the results. It should be noted that even with deterministic service time of 1000 ms, DWG tries to generate a query with a service that is closest to 1000 ms and therefore, the actual service times may vary slightly. Hence, the workloads may have a natural variation in the response times.

We use deterministic inter-arrival time for the primary workload and random (exponential distribution) inter-arrival time for the secondary workload to ensure that both the workloads are not tightly synchronized. On average, the inter-arrival time of the secondary workload will be 300 ms, but during some bursts the inter-arrival time may be lower and during others the inter-arrival time may be higher. Therefore, during some bursts, the CPU utilization for the secondary workload, $W_B$, will be higher and hence, the total CPU utilization will be greater than 4. The experiment in the next section shows whether these CPU-intensive bursts of the test workloads, $W_A$ and $W_B$, result in an overloaded environment on the whole or not.

| **Test Workloads** | **Workload Streams** | $T_S$ **[value (ms), distribution]** | $T_A$ **[value (ms), distribution]** |
|---|---|---|---|
| Primary | $W_A$ | 1000, deterministic | 2000, deterministic |
| Secondary | $W_B$ | 1000, deterministic | 300, exponential |

**Table 1: Test workloads $W_A$ and $W_B$ configurations**

## 4.3 Experiment 1: Effect of $W_B$ on $W_A$

As explained in Chapter 1, our controller is targeted at achieving performance objectives for the primary workload $W_A$ in a problem scenario where the secondary workload $W_B$ overloads the system and competes with $W_A$ for CPU resources. Therefore, in order to examine the effect of $W_B$ on $W_A$, we conducted this characterization experiment. In this experiment, we compare the performance of each workload when run in isolation with the performance of the workloads when run together. Essentially, we compare the performance of $W_A$ when there is no CPU contention with the performance of $W_A$ in an overloaded system in which there is there is competition for CPU resources.

In this experiment, we performed three runs with a runtime of 96 minutes each. First, $W_A$ is run in isolation and the response time average is measured every 30 seconds (for calculation of variance in the response time average measurements) over the run. Second, $W_B$ is run in isolation and the response time average is measured every 30 seconds over the run. Third, $W_A$ and $W_B$ are run together and their response time averages are measured every 30 seconds over the run. The first two runs serve as the baseline measure for the third run. The third run is for examining whether the workloads together overload the system, which is confirmed by a significant increase in response time averages of both the workloads.

Figure 5 shows the averages of the response time average measurements of all the runs. The response time average of $W_A$ when run in isolation is nearly 1000 ms with a very low standard deviation of 0.7. This is because of using a deterministic service time of 1000 ms for $W_A$, which confirms that the response time of $W_A$ does not have a significant natural variation. When $W_A$ and $W_B$ are run together, we see a significant deterioration in the performances of $W_A$ and $W_B$. Most importantly, the response time average of the primary workload $W_A$ increased to 14550 ms, which is 14 times that of $W_A$ when run in isolation. This result confirms that the secondary workload $W_B$ competes for CPU resources with the primary workload $W_A$, thereby deteriorating the response time average of the primary workload $W_A$. Therefore, the workloads $W_A$ and $W_B$ when run together create a good test instance of our problem scenario, on which our admission controller mechanism can be tested.

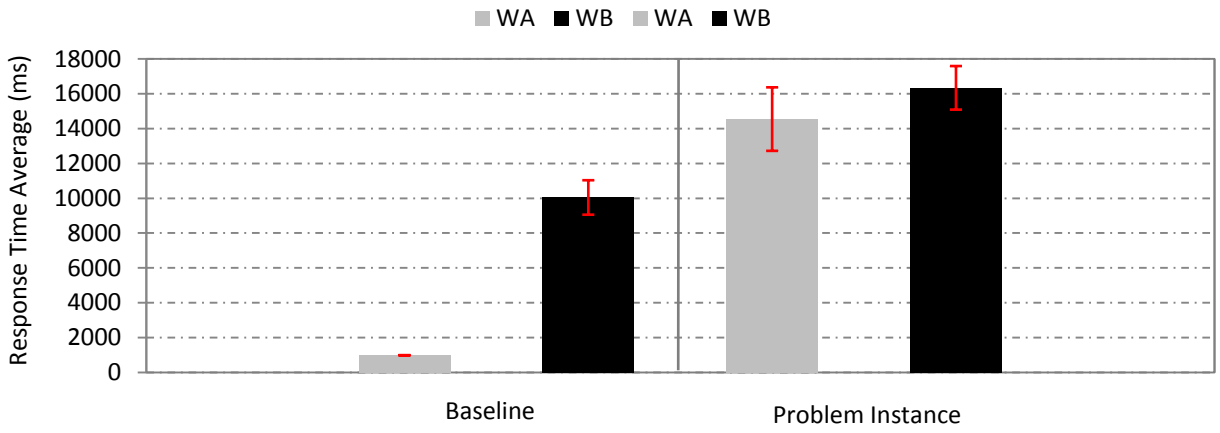



**Figure 5: Baseline is $W_A$ and $W_B$ when run in isolation. Problem instance is $W_A$ and $W_B$ when run together. The bars show response time averages and error bars show standard deviations in the response times.**

## 4.4 Experiment 2: Effectiveness of Admission Control

Before testing the controller, we must confirm whether admission control is an effective way to control the response time of the primary workload $W_A$. Specifically, in this experiment, we determine whether adjusting the concurrency threshold is an effective way to control the response time of $W_A$. We illustrate how changing the concurrency threshold on the secondary workload $W_B$ affects the response time average of primary workload $W_A$.

In this experiment, we run the test workloads with a fixed concurrency threshold value for $W_B$ and measure the response time average of $W_A$ every 30 seconds, and then repeat the experiment for different threshold values. The averages of the response time average measurements collected for each threshold value, 1 to 9 (chosen arbitrarily), are plotted in Figure 6(a). For each threshold, the standard deviation of response time averages is shown as error bars in the figure. For better understanding of the trends in the values, we present the response time average values and their standard deviation values in Table 2. It is to be noted that the response time average will increase further with increase in concurrency threshold beyond the value 9 till the response time average value of 14550 ms (obtained in Section 4.3).

We also show the effect of the concurrency threshold on the throughput of the secondary workload $W_B$, in Figure 6(b). The figure shows that the throughput of the secondary workload increases till the

value 3.2 and then levels off at the same value. This is because the average CPU utilization of the secondary workload, as explained in Section 4.2, is 3.33. With the concurrency threshold being an upper bound on the number of concurrent queries that can execute at a time, the secondary workload was able to execute only as many queries as the threshold value till it reached its maximum concurrency at threshold 4. At concurrency threshold 4 and higher, the secondary workload was able to run close to its maximum concurrency of 3.33.

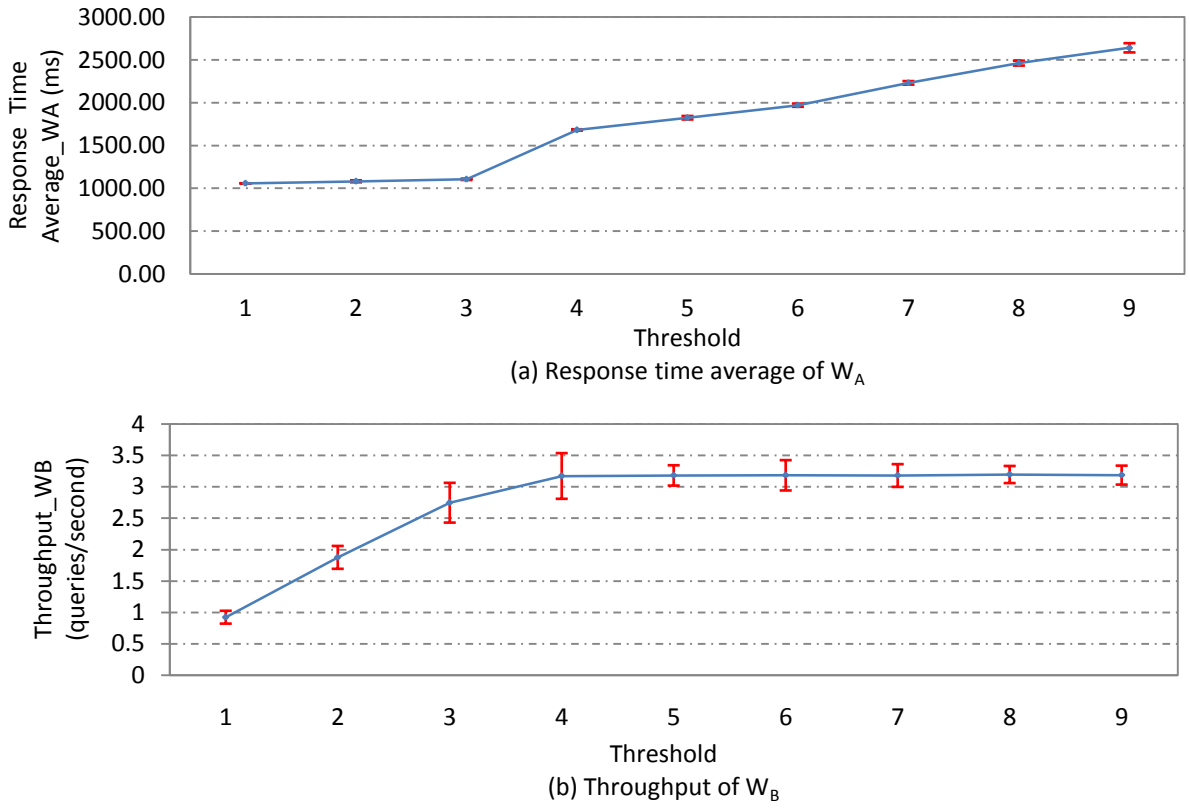



**Figure 6: Sensitivity to concurrency threshold on $W_B$. (a) shows response time average of $W_A$ for each concurrency threshold on $W_B$. (b) shows throughput of $W_B$ for each concurrency threshold on $W_B$. Error bars indicate standard deviation in the measurements at each concurrency threshold.**

| Concurrency threshold (C) | Response time average | Standard deviation ($\sigma_C$) |
|---|---|---|
| 1 | 1058 | 1.38 |
| 2 | 1082 | 6.84 |
| 3 | 1105 | 7.46 |
| 4 | 1682 | 106.14 |
| 5 | 1824 | 135.70 |
| 6 | 1970 | 149.55 |
| 7 | 2231 | 172.56 |
| 8 | 2462 | 189.78 |
| 9 | 2641 | 210.31 |

**Table 2: Response time average and standard deviation of $W_A$ for each concurrency threshold C from Figure 6(a)**

In Figure 6(a), there are two slopes in the trend of the response time averages of $W_A$. The figure shows that an increase in concurrency threshold value from 1 to 3 resulted in a barely noticeable increase in the response time average of $W_A$. The slope of the (best fit) line is 23. For increase in concurrency threshold value from 4 to 9, there was a significant increase in the response time average of $W_A$. The slope of the (best fit) line is 225, which is nearly 10 times that of the slope for thresholds 1 to 3. The following is the explanation for the two distinct trends:

1. The trend of thresholds 1 to 3 exemplifies a *no-CPU-contention environment*; the total concurrency of both the workloads together in the system is less than 4, which is number of CPU cores in the system. Therefore, there is one-to-one mapping between queries and each CPU core. Each query will have a dedicated CPU core. Hence, each query will have negligible wait time $T_W$. Therefore, the changing concurrency threshold on $W_B$ isn`t reflected much on the response time average of $W_A$.
2. The trend of thresholds 4 to 9 exemplifies a *CPU-contention environment*; the total number of concurrent queries of both the workloads together in the system can be more than 4

sometimes. During the bursts in which the inter-arrival time of $W_B$ is smaller than 300 ms, the queries that exceed the concurrency threshold applied are queued. Hence, as and when the number of concurrent $W_B$ queries drops below the threshold, there are always queued queries ready to run and increase the number of concurrent $W_B$ queries to the threshold value. Therefore, effectively, there can be threshold number of $W_B$ queries running concurrently in the system. Hence, there can be many-to-one mapping between queries and each CPU core. The queries are multiplexed between the CPU cores through context-switching and scheduling. Therefore, with increase in concurrency, there will be significant increase in context switches for each query and hence, there will be significant increase in CPU wait time $T_W$ for each query. Therefore, each unit value change in concurrency threshold on $W_B$ results in a significant change in the response time average of $W_A$.

Apart from these two significant trends, there is a steep slope from threshold value 3 to 4. This is due to a spike in the response time average of $W_A$ at threshold 4. At threshold 4, $W_B$ performs at its maximum concurrency and therefore, tries to keep more than 3 CPU cores busy, on average. Since $W_A$ requires at least one CPU core, it faces significant competition from $W_B$ for that one CPU core because there are only 4 CPU cores in the system. Hence, the response time average of $W_A$ increases steeply at threshold 4.

Similar to the significant trends in response time averages of $W_A$, there are two trends for the variance in the response time measurements of the primary workload $W_A$ (in Table 2). The trend for standard deviation $\sigma_C$ for each concurrency threshold $C$ is as follows:

1. Thresholds 1 to 3: As it is expected with a stable primary workload with no significant natural variation in a no-CPU-contention environment, the figure shows small standard deviations for these thresholds. For example, $\sigma_1$ = 1.38, $\sigma_2$ = 6.84 and $\sigma_3$ = 7.46.

2. Thresholds 4 to 9: The response time average measurements aren't stable enough because the measurements are dominated by the variance brought in due to resource contention, which brings in context switching and scheduling overhead. For example, $\sigma_4$ = 106.14 and $\sigma_5$ = 135.70 which are nearly 10 times that of threshold 1.

## 4.5 Controller experiments with stable workload and fixed objective

The experiments in this section will show the controller's performance in achieving fixed response time objectives on stable workloads. The response time objective to be achieved for $W_A$ and the workloads' characteristics remain unchanged during the experiment. The purpose of these experiments is to demonstrate the effectiveness of the controller in achieving response time objectives for $W_A$.

In all the controller experiments, we use the response time averages of $W_A$ obtained from Figure 6(a) (shown in Table 3) as objectives in all the evaluation experiments. For example, if a response time average objective of 1105 ms is chosen for the controller to achieve, we expect the controller's output to reach concurrency threshold of value 3 and stay on it.

| Response time objective (R) | Expected concurrency threshold |
|---|---|
| 1058 | 1 |
| 1082 | 2 |
| 1105 | 3 |
| 1682 | 4 |
| 1824 | 5 |

**Table 3: $R_S$ is the response time objectives for $W_A$ used in the experiments and expected concurrency threshold is the threshold value that is expected to be chosen by the controller.**

The controller experiments presented in this section are experiments with a properly tuned controller constant $K_I$ and a properly tuned control interval $I$. For each experiment, the controller constant $K_I$ and control interval $I$ were chosen experimentally, based on trial and error. The tuning of these two input parameters of the controller will be discussed further in Section 4.8. For all experiments, we used an arbitrary polling interval $t$ of 10 seconds which is small enough to give the controller the granularity to poll close to the minimum number of completed primary workload queries specified as the control interval $I$.

For each controller experiment, four graphs are presented to show the dynamics of the workloads as a function of time:

- The first graph shows the response time average *R(i)* of primary workload measured after each control interval. We expect the primary workload to achieve its response time objective $R_S$ with minimal overshoot and oscillation and stabilize on the objective.
- The second graph shows the controller output *C(i)*, the new, calculated concurrency threshold the controller applies on secondary workload after each control interval. We expect it to reach the expected concurrency threshold corresponding to the objective shown in Table 3 with minimal overshoot and oscillation and stabilize on the threshold.
- The third graph shows the throughput of secondary workload during each control interval. We expect it to increase when the concurrency threshold applied on the secondary workload increases and decrease when the concurrency threshold applied on the secondary workload decreases.
- The fourth graph shows the response time average of the secondary workload measured after each control interval. We expect it to decrease with an increase in the concurrency threshold applied on the secondary workload and increase with a decrease in the concurrency threshold applied on the secondary workload.

### 4.5.1 Controller Experiment 1: $R_S = 1082$, $K_I = 0.01$, $I = 20$

In this experiment, we use a response time average objective $R_S$ of 1082 ms. The purpose of this experiment is to test whether the controller is able to achieve an objective from the no-CPU-contention environment. We expect the controller to stabilize on concurrency threshold 2 with minimal overshoot and oscillation.

We perform this experiment with a controller constant $K_I$ of value 0.01 and a control interval *I* of a minimum of 20 primary workload queries. Figure 7 shows the results of this experiment. The controller output graph (in Figure 7(b)) shows that the controller output *C(i)* reaches the expected concurrency threshold 2 in 280 seconds (7 control steps, each after an interval of 40 seconds) and as a result, the response time average *R(i)* (in Figure 7(a)) also reaches the desired objective 1082 ms. The figure shows that the controller understands that if the response time average *R(i)* of the

primary workload is less than the objective $R_S$, then the controller should increase the concurrency threshold on the secondary workload so that more secondary workload queries can be executed, thereby increasing the CPU utilization and consequently, increasing *R(i)* towards $R_S$.

The minor oscillations (step downs) in *C(i)* observed in the controller output graph (in Figure 7(b)) are due to variance in the response time average measurements. This sensitivity can be reduced by reducing the controller constant $K_I$.

Therefore, given proper values for input parameters $K_I$ and *I*, this experiment shows that the controller is able to achieve the response time objective $R_S$ of value 1082 ms and perform well in a no-CPU-contention environment with minimal oscillation.

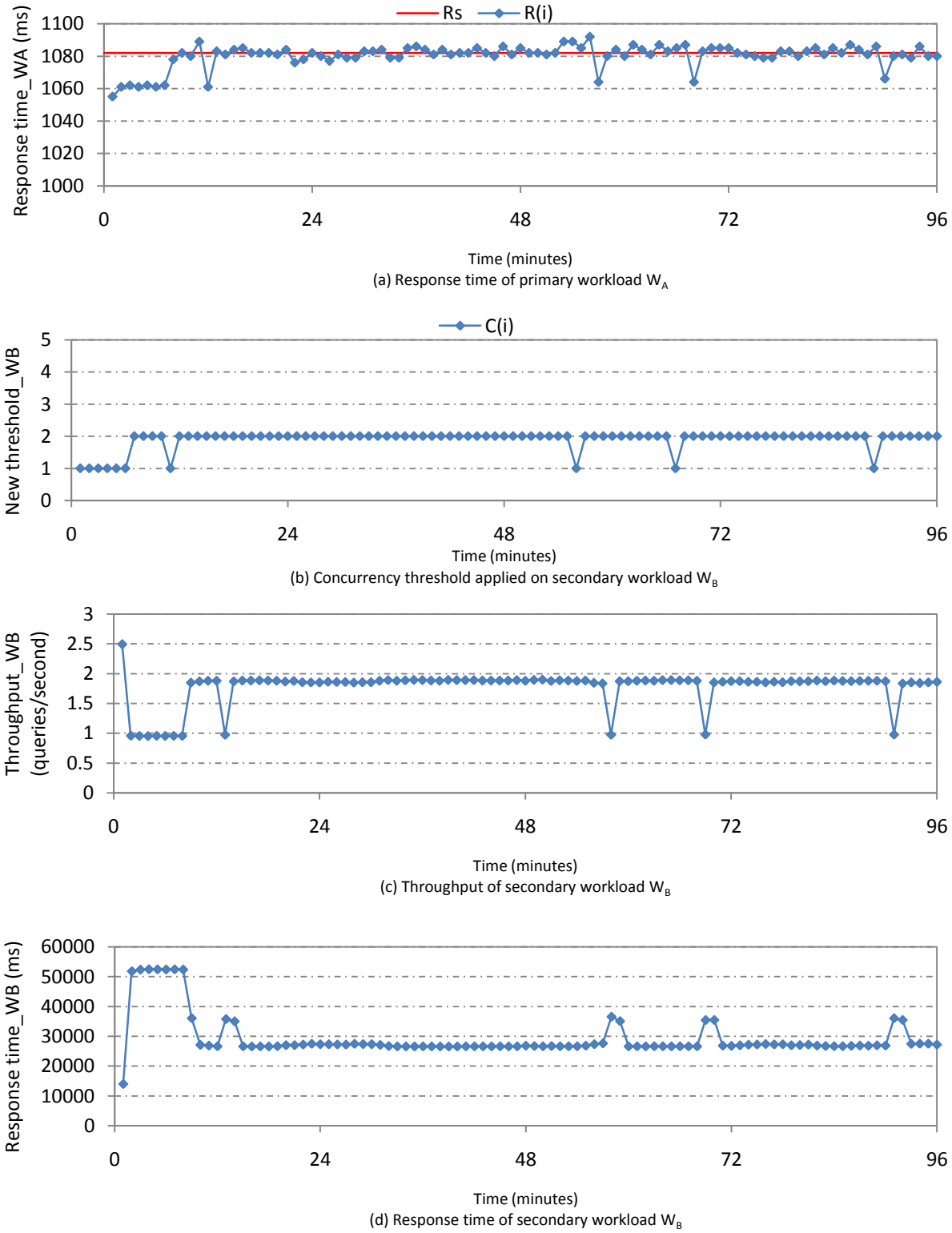



**Figure 7: Controller experiment results with inputs $R_S$ = 1082ms, $K_I$ = 0.01, I = 20**

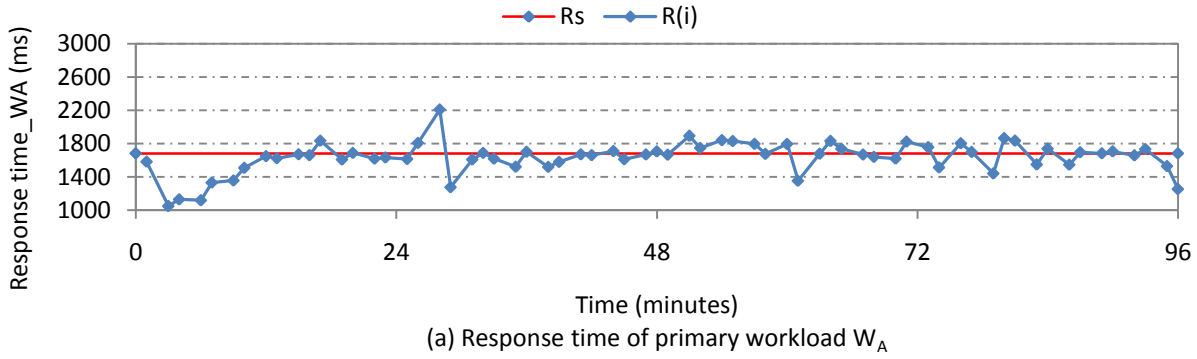
### 4.5.2 Controller Experiment 2: $R_S$ = 1682ms, $K_I$ = 0.001, I = 40

In this experiment, we use a response time average objective $R_S$ of 1682 ms. The purpose of this experiment is to test whether the controller is able to achieve a response time average objective from the CPU-contention environment. We expect the controller to stabilize on concurrency threshold 4 with minimal overshoot and oscillation.

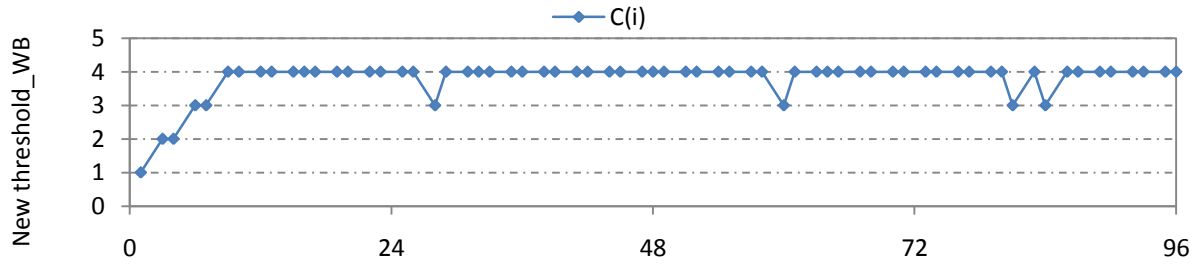
We perform this experiment with a controller constant $K_I$ of value 0.001 and a control interval $I$ of a minimum of 40 completed primary workload queries. Figure 8 shows the results of this experiment. The controller output graph (Figure 8(b)) shows that the controller output *C(i)* smoothly climbs to the expected threshold 4 in 480 seconds (6 control steps, each after an interval of 80 seconds). Correspondingly, the response time average *R(i)* (in Figure 8(a)) also steadily climbs to the desired objective 1682 ms.

Compared to Controller Experiment 1, a smaller controller constant $K_I$ of value 0.001 and a longer control interval $I$ of a minimum of 40 completed primary workload queries worked well in this experiment because the response time objective 1682 ms belongs to the CPU-contention environment. For the CPU-contention environment, as explained in Experiment 2, the (slope of) change in response time average of primary workload for a unit change in concurrency threshold on secondary workload is higher. This results in larger changes in response time when the controller changes the concurrency threshold. Therefore, a smaller controller constant $K_I$ compensates for the larger changes in response time that the controller makes. In addition, for the CPU-contention environment, the variance in the response time averages of the primary workload is higher. Therefore, a longer control interval $I$ dampens the variance and allows the controller to stay on the response time objective 1682 ms with minimal oscillation.

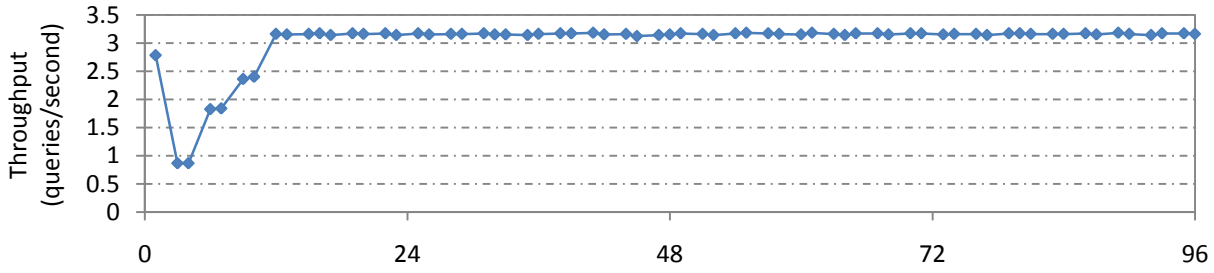
Therefore, given appropriate values for input parameters $K_I$ and $I$, this experiment shows that the controller is able to achieve the response time objective $R_S$ of value 1682 ms and perform well in a CPU-contention environment with minimal oscillation.



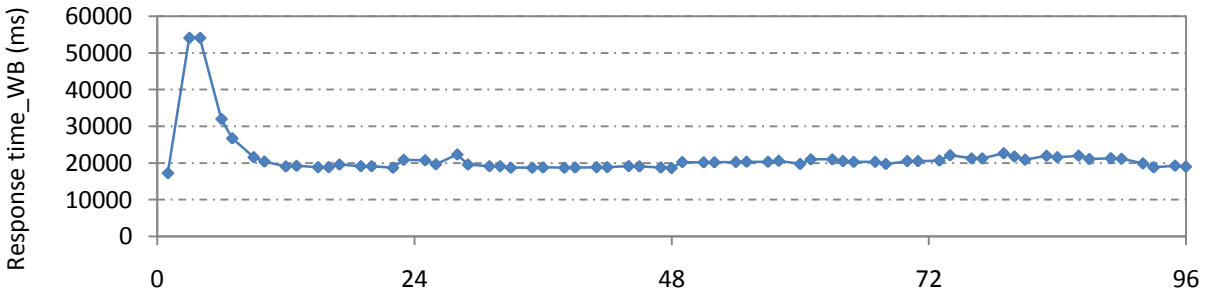

(a) Response time of primary workload $W_A$




(b) Concurrency threshold applied on secondary workload $W_B$




(c) Throughput of secondary workload $W_B$




(d) Response time of secondary workload $W_B$

**Figure 8: Controller experiment results with inputs: $R_S$ = 1682ms, $K_I$ = 0.001, I = 40**

### 4.5.3 Conclusion

The experiments in this section show that our adaptive admission controller can achieve response time objectives for the primary workload by applying admission control on the secondary workload, provided that appropriate values are set for controller constant $K_I$ and control interval $I$. The controller is able to perform well without any performance problems in environments without CPU contention in Experiment 1 and with CPU contention in Experiment 2.

## 4.6 Controller Experiments with Stable Workload and Changing Objective

In this section, we test our controller in a scenario in which the response time objective changes. In these experiments, the response time objective $R_S$ of primary workload is changed half-way through the experiment. The purpose of these experiments is to show how the controller automatically adapts to changes in the response time objective.

In these experiments, when the response time objective $R_S$ changes, it results in significant error in the comparison of the measured response time average $R(i)$ of the primary workload and the objective $R_S$. Therefore, the controller calculates and applies a new threshold on the secondary workload and then the response time average of the primary workload changes accordingly. Essentially, the change is initiated by the controller output that consequently directs the running response time average towards the objective.

For experiments in this section, after experimental tuning, we use a controller constant $K_I$ of value of 0.01 for objectives from the no-CPU-contention environment. We use a $K_I$ of value 0.001 for objectives from the CPU-contention environment. If we have objectives from both the environments, we use a $K_I$ value of 0.01/6 which is midway between values 0.01 and 0.001. Similarly, we use a control interval $I$ of a minimum of 20 primary workload queries for objectives from a no-CPU-contention environment and a minimum of 40 primary workload queries when there is an objective from a CPU-contention environment involved.

### 4.6.1 Controller Experiment 3: $R_S$ = 1058ms -> 1082ms

In this experiment, the controller is tested for a response time objective change of a small magnitude from 1058 ms to 1082 ms. The challenge for the controller in this experiment is that we

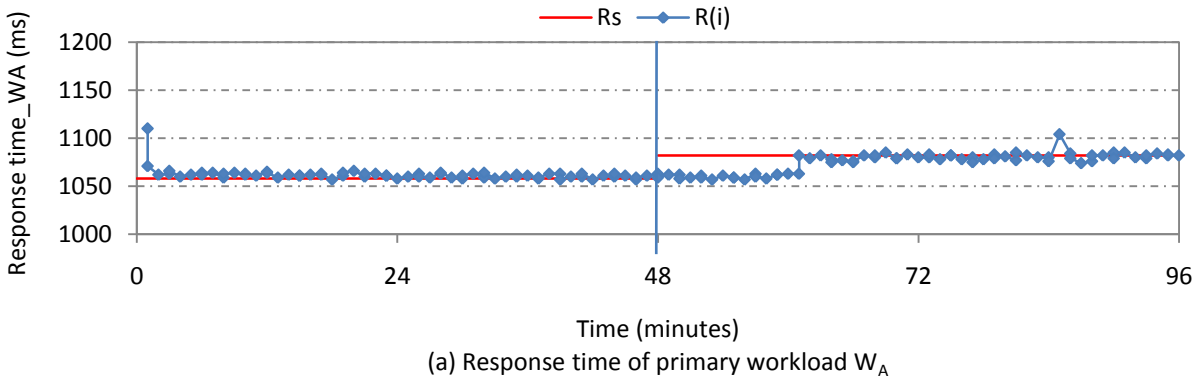
change from a response time objective corresponding to a lower concurrency threshold to a response time objective corresponding to a higher concurrency threshold. Therefore, when the objective changes, we expect the controller output to increase from threshold 1, which is the expected concurrency threshold for objective 1058 ms, to threshold 2, which is the expected concurrency threshold for objective 1082 ms, with minimal overshoot and oscillation.

We use a controller constant $K_I$ of value 0.01 and a control interval $I$ of a minimum of 20 primary workload queries because both the objectives 1058 ms and 1082 ms correspond to thresholds from the no-CPU-contention environment.

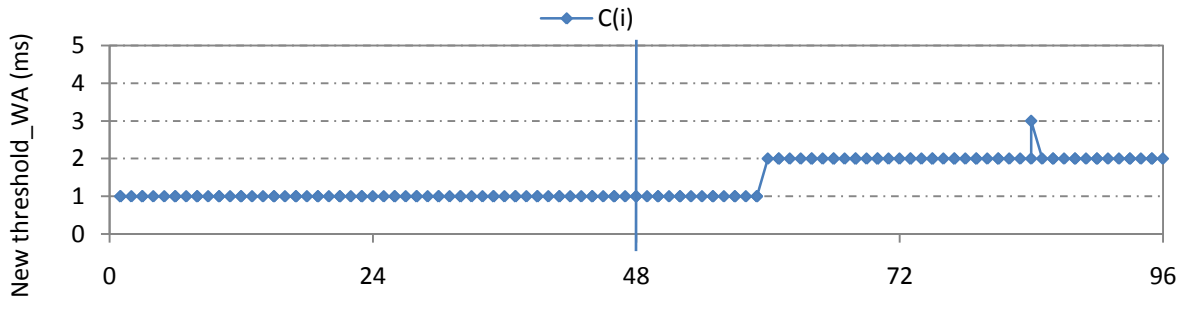
Figure 9 shows the results of this experiment. The controller output graph (in Figure 9(b)) shows that after the objective changes, the controller output *C(i)* successfully increases from threshold 1 to threshold 2. Therefore, the controller understands that if the response time objective of $W_A$ increases, then it has to increase the concurrency threshold on $W_B$ so that more $W_B$ queries can execute, thereby increasing $W_B$'s CPU utilization and consequently, increasing the response time average *R(i)* of $W_A$ (in Figure 9(a)) towards the objective $R_S$.

The figure shows that the controller successfully achieved both the objectives with minimal overshoot and oscillation. However, the controller output $C(i)$ took a long time of 480 seconds (12 control steps, each after an interval of 40 seconds) to converge onto the expected threshold 2. This is because of a transient spike in the response time average of $W_A$ at the first control step. The spike is due to test workload's start up disturbance. The controller measured a high response time average and as a result, the accumulated error of the controller significantly reduced to negative error and continued to be there because it was still achieving the objective of 1058 ms by applying the minimum concurrency threshold value of 1 on $W_B$. Therefore, when the objective changed, it took a long time for the accumulated error to increase from the negative error and accumulate enough positive error for the controller output *C(i)* to increase up to threshold 2. This shows that such transient disturbances in the system can lengthen the convergence time for the controller. The convergence time can be decreased by increasing the controller constant $K_I$ for the controller to take larger control steps or decrease the control interval $I$ for the controller to take more control steps per unit time.

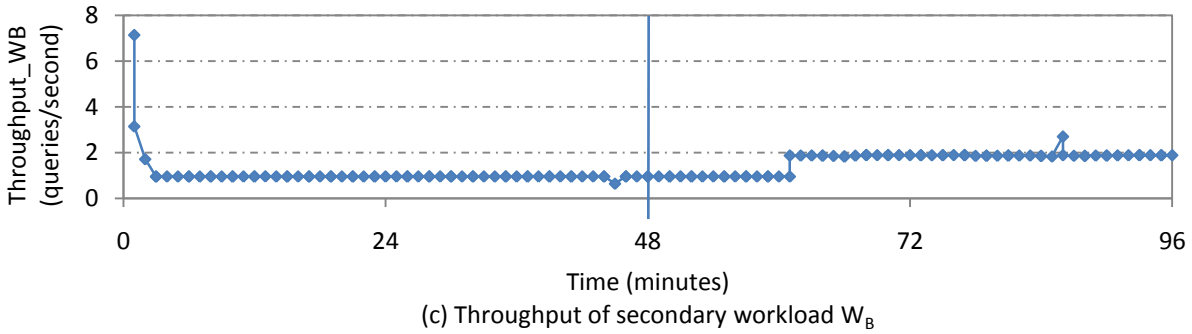
This experiment shows that the controller is able to automatically handle a response time objective increase by a small magnitude without any performance problems of overshoot and oscillation.



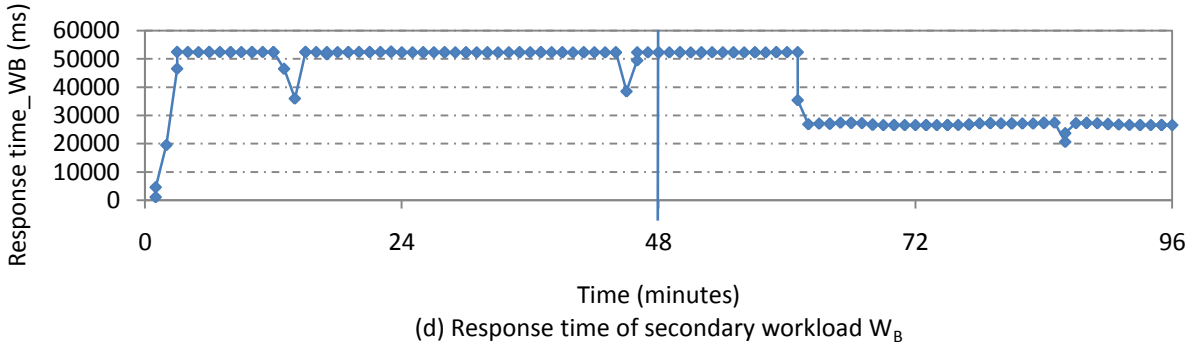

(a) Response time of primary workload $W_A$




(b) Concurrency threshold applied on secondary workload $W_B$




(c) Throughput of secondary workload $W_B$




(d) Response time of secondary workload $W_B$

**Figure 9: Controller experiment results with inputs: $R_S$ = 1058ms->1082ms, $K_I$ = 0.01, I = 20**

### 4.6.2 Controller Experiment 4: $R_S$ = 1105ms -> 1058ms

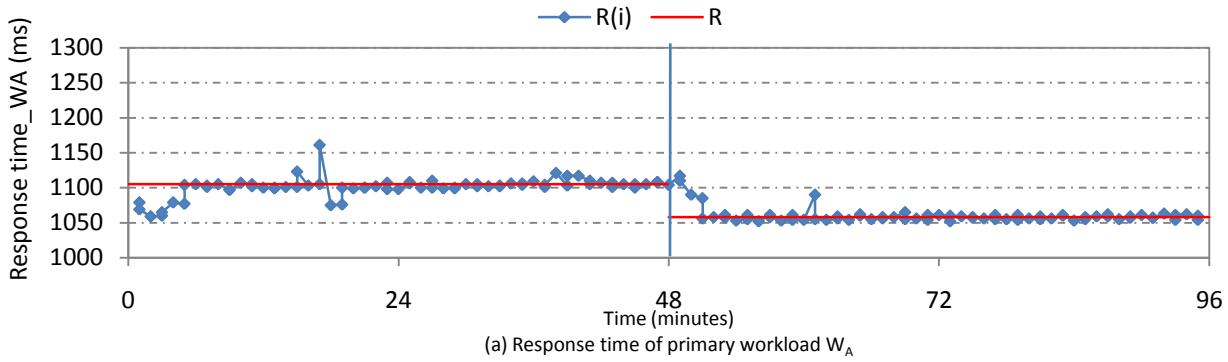
In this experiment, we tested the controller for a response time objective decrease of a small magnitude from 1105 ms to 1058 ms. The challenge for the controller in this experiment is that we change from a response time objective corresponding to a higher concurrency threshold to a response time objective corresponding to a lower concurrency threshold. Therefore, when the objective changes, we expect the controller output to decrease from concurrency threshold 3, which is the expected concurrency threshold for objective 1105 ms, to threshold 1, which is the expected concurrency threshold for objective 1058 ms.

Similar to previous experiment, we use a controller constant $K_I$ of 0.01 and a control interval $I$ of a minimum of 20 primary workload queries in this experiment.

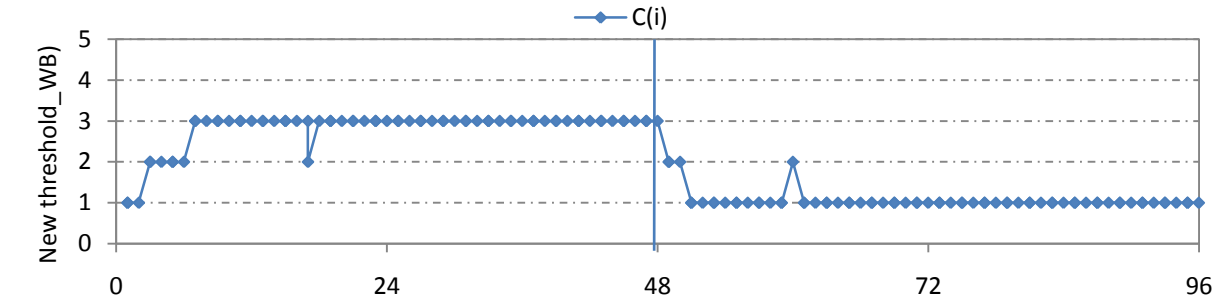
Figure 10 shows the results of this experiment. The controller output graph (in Figure 10(b)) shows that after the objective changes, the controller output *C(i)* successfully decreases from threshold 3 to threshold 1. This shows that the controller understands that if the response time objective of $W_A$ decreases, then it has to decrease the concurrency threshold on $W_B$ so that fewer $W_B$ queries execute in the system, thereby decreasing $W_B$'s CPU utilization and consequently, decreasing the response time average of $W_A$ towards the objective $R_S$.

The figure shows that the controller successfully achieved both of the response time objectives without overshoot and oscillation. The controller output graph in the figure shows that before the objective changed, the controller output *C(i)* converged onto the expected threshold 3 in 280 seconds (7 control steps, each after an interval of 40 seconds) and after the objective changed, the controller output converged onto the expected threshold 1 in 120 seconds (3 control steps). Correspondingly, the response time average *R(i)* of $W_A$ (in Figure 10(a)) also steadily converged onto the respective objective $R_S$.

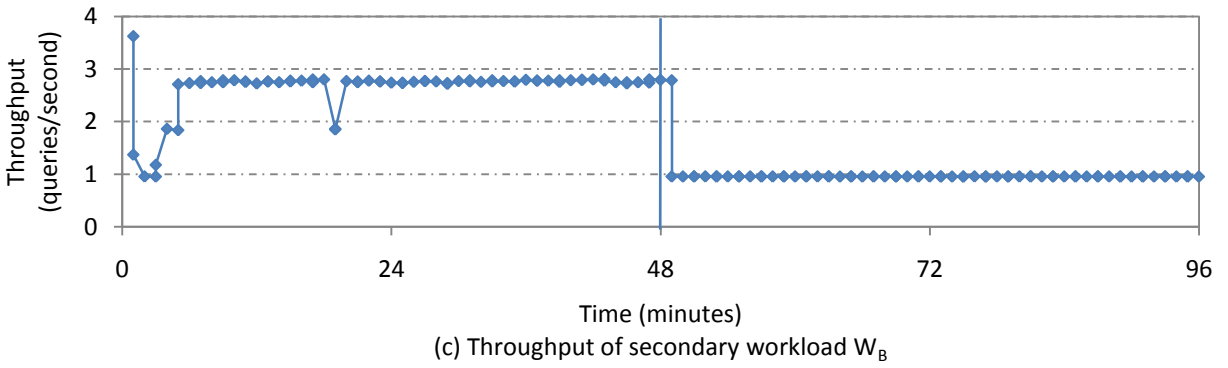
This experiment shows that the controller is able to dynamically handle a response time objective decrease by a small magnitude without any performance problems.



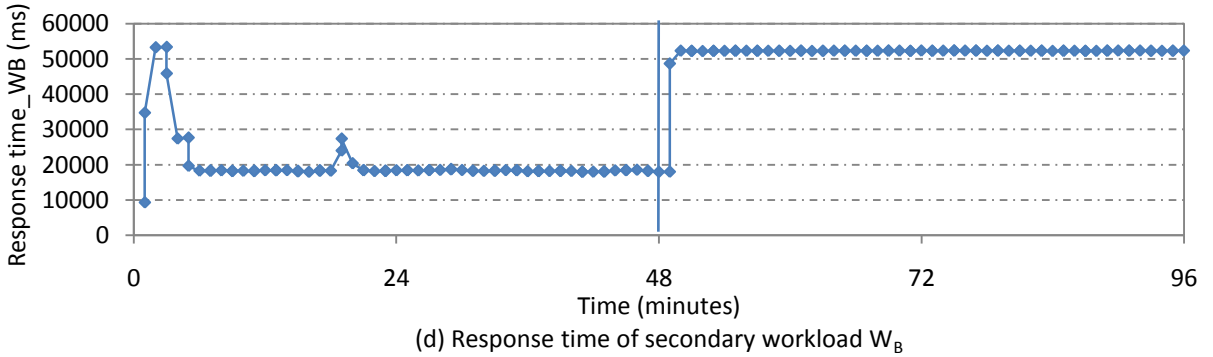

(a) Response time of primary workload $W_A$




(b) Concurrency threshold applied on secondary workload $W_B$




(c) Throughput of secondary workload $W_B$




(d) Response time of secondary workload $W_B$

**Figure 10: Controller experiment results with inputs: $R_S$ = 1105ms->1058ms, $K_I$ = 0.01, I = 20**

### 4.6.3 Controller Experiment 5: $R_S$ = 1824ms -> 1058ms

In this experiment, we tested the controller for a response time objective change of a large magnitude from 1824 ms to 1058 ms. When the objective changes, we expect the controller output to decrease from concurrency threshold 5, which is the expected concurrency threshold for objective 1824 ms, to concurrency threshold 1, which is the expected concurrency threshold for objective 1058 ms.

We know that a lower controller constant $K_I$ of value 0.001 works for the objective 1824 ms because it belongs to the CPU-contention environment. We know that a higher controller constant $K_I$ of value 0.01 works for the objective 1058 ms because it belongs to the resource-sufficient environment. In this experiment, we have both the objectives and therefore, we use a $K_I$ of value in between 0.01 and 0.001 that works reasonably well for both the objectives. We found a $K_I$ of a value 0.01/6 to work the best. We use a control interval $I$ of a minimum of 40 primary workload queries in this experiment.

Figure 11 shows the results of this experiment. The controller output graph (in Figure 11(b)) shows that when the objective decreases by a large magnitude, the controller output *C(i)* drops and continues to drop until the expected threshold 1. This shows that the controller continues to make changes to the concurrency threshold as long as there is any error in the comparison of the response time average *R(i)* and the response time objective $R_S$. The controller constantly strives to achieve zero error and consequently, it strives to achieve the objective $R_S$.

The results in the figure shows there were no performance problems of overshoot and oscillation due to change in response time objective. The controller successfully achieved both the response time objectives. The controller output graph in the figure shows that before the objective changed, the controller output *C(i)* converged onto the expected threshold 5 in 320 seconds (4 control steps, each after an interval of 80 seconds). After the objective changed, for objective 1058 ms from the no-CPU-contention environment, as expected with a smaller control constant $K_I$ and a longer control interval $I$, the controller output *C(i)* took a longer time of 1440 seconds (18 control steps) to converge onto the expected threshold 1 in comparison to the previous experiments with objective 1058 ms. Correspondingly, the response time average *R(i)* of $W_A$ (in Figure 11(a)) also steadily converged onto the respective objective $R_S$.

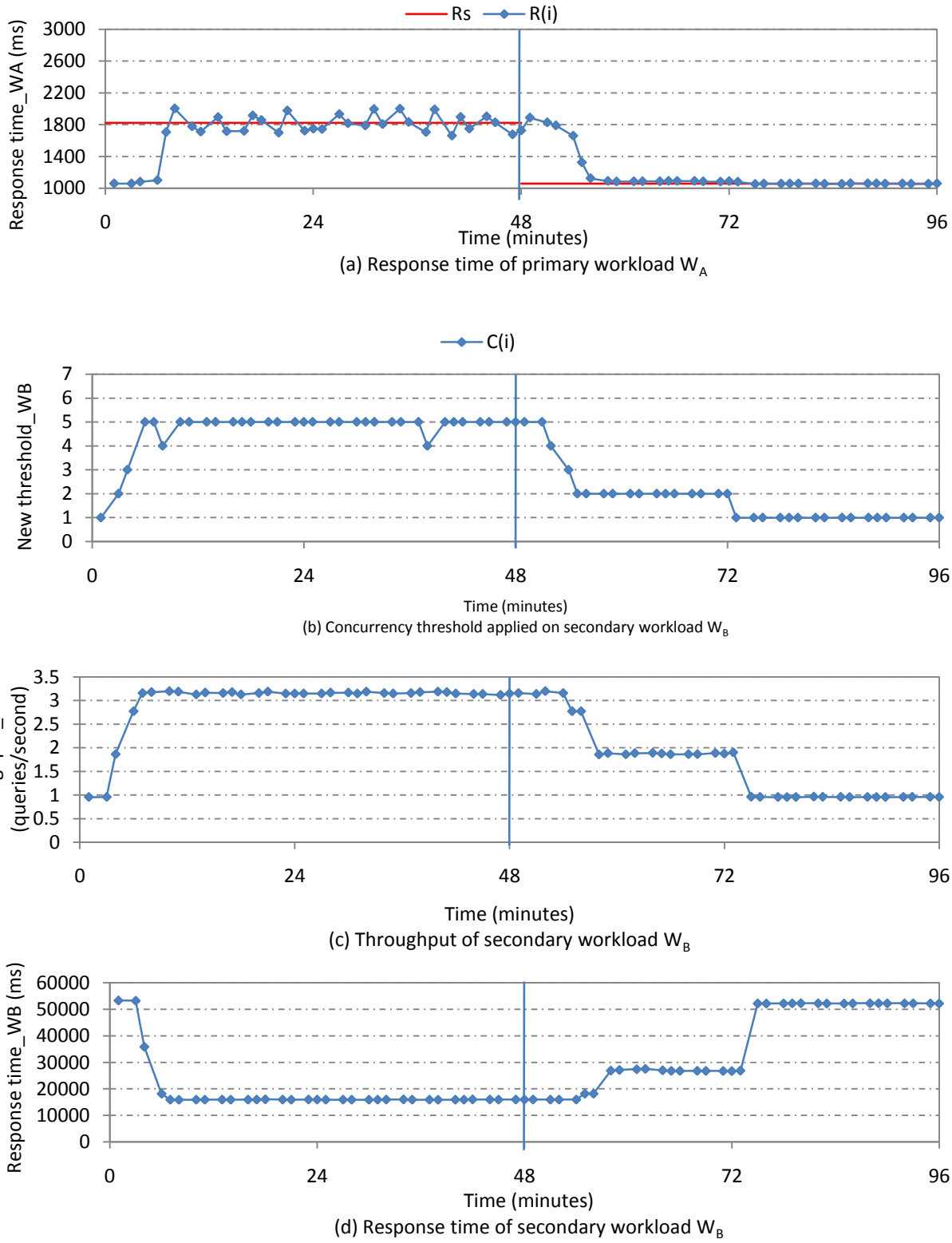



**Figure 11: Controller experiment results with inputs: $R_S$ = 1824ms->1058ms, $K_I$ = 0.01/6, I = 40**

### 4.6.4 Conclusion

All the experiments in this section show that the controller can dynamically handle a change in the response time objective $R_S$. When the objective changes, the controller measures the change through the error calculated when comparing the response time average *R(i)* of the primary workload with the response time objective $R_S$. As a result, the controller makes appropriate changes to the concurrency threshold *C(i)* on the secondary workload and thereby, regulating the number of queries executing in the system so that the response time average *R(i)* is directed towards the objective $R_S$. There were no performance problems of overshoot and oscillation due to a change in the response time objective during the length of the experiments.

## 4.7 Controller Experiments with Changing Workloads and Fixed Objective

In this section, we test the adaptability of controller to a change in workload on the system. In these experiments, the workload is changed after every 1/3rd of the experiment. Specifically, we test the controller`s ability to adapt to a change in CPU utilization due to change in the total number of concurrent queries running in the system.

We design a workload stream $W_C$ to add to the primary workload in these experiments. Note that we add the stream to the primary workload and not to the secondary workload because adding a stream to the secondary workload will not be useful towards our intention to change the total number of concurrent queries running in the system. Any added concurrency to the secondary workload will end up queuing due to concurrency threshold, resulting in no increase in the CPU utilization.

For workload stream $W_C$, we choose a deterministic service time of 1000 ms and a deterministic inter-arrival time of 4000 ms. When this workload stream is added after every 1/3rd of the experiment, it should add to the CPU utilization on the system by keeping another 0.25 CPUs busy.

| **Workload Stream** | $T_S$ **[value (ms), distribution]** | $T_A$ **[value (ms), distribution]** |
|---|---|---|
| $W_C$ | 1000, deterministic | 4000, deterministic |

**Table 4: Test workload $W_C$ configuration**

In these experiments, a change in workload results in change in the response time average *R(i)* of the primary workload and consequently, results in significant error in the comparison of *R(i)* and the response time objective $R_S$. Due to increased error, the controller output *C(i)* changes. Contrary to the response time objective change experiments, in these experiments, the change is initiated by the response time average *R(i)* of the primary workload that directs the controller output *C(i)* on the secondary workloads.

In these experiments, since we work with changing workload, we also get to evaluate the controller for a response time objective $R_S$ that does not correspond exactly to any concurrency threshold. We conduct all the experiments with an arbitrarily chosen response time objective of 1105 ms.

### 4.7.1 Controller Experiment 6: Workload increase

In this experiment, the workload on the system is increased by a large magnitude after every 1/3$^{rd}$ of the experimental runtime. We add workload stream $W_C$ to the primary workload $W_A$ at the beginning of the experiment and after every 32 minutes into the experiment. Therefore, the workloads in the three phases of the experiment are shown in Table 5.

| Phase | Primary workload | Secondary workload |
|---|---|---|
| 1 | $W_A+W_C$ | $W_B$ |
| 2 | $W_A+W_C+W_C$ | $W_B$ |
| 3 | $W_A+W_C+W_C+W_C$ | $W_B$ |

**Table 5: Workloads in each phase of Experiment 6**

The purpose of this experiment is to study how the controller adapts to workload increases. The challenge in this experiment is that we change from a workload with the response time objective 1105 ms corresponding to a higher concurrency threshold value to a workload with the response time objective 1105 ms corresponding to a lower concurrency threshold. Therefore, when the workload

increases, we expect the controller output to decrease and converge onto the right concurrency threshold corresponding to the objective or toggle between two thresholds, between which the objective exists.

We perform this experiment with a controller constant $K_I$ of value 0.01/6 and a control interval $I$ of a minimum of 20 primary workload queries. Figure 12 shows the results of this experiment. In Figure 12(a), in the first phase, the response time objective 1105 ms corresponds to concurrency threshold 2 and therefore, the controller output *C(i)* (in Figure 12(b)) settles on threshold 1. The controller output *C(i)* converges onto the expected threshold 2 in 460 seconds. In the second phase, the objective 1105 ms shifts to corresponding to a concurrency threshold value lying in between thresholds 1 and 2 and therefore, *C(i)* oscillates between the thresholds 1 and 2. In the third phase, the objective 1105 ms shifts to corresponding to concurrency threshold 1 and therefore, the controller output settles on threshold 1. The effect of the shift due to workload changes can be seen in the throughput and the response time graphs of the secondary workload $W_B$ too.

This experiment shows that the controller is able to dynamically adapt to increase in workload, i.e. increase in CPU utilization, without any performance problems due to a change in the workload.

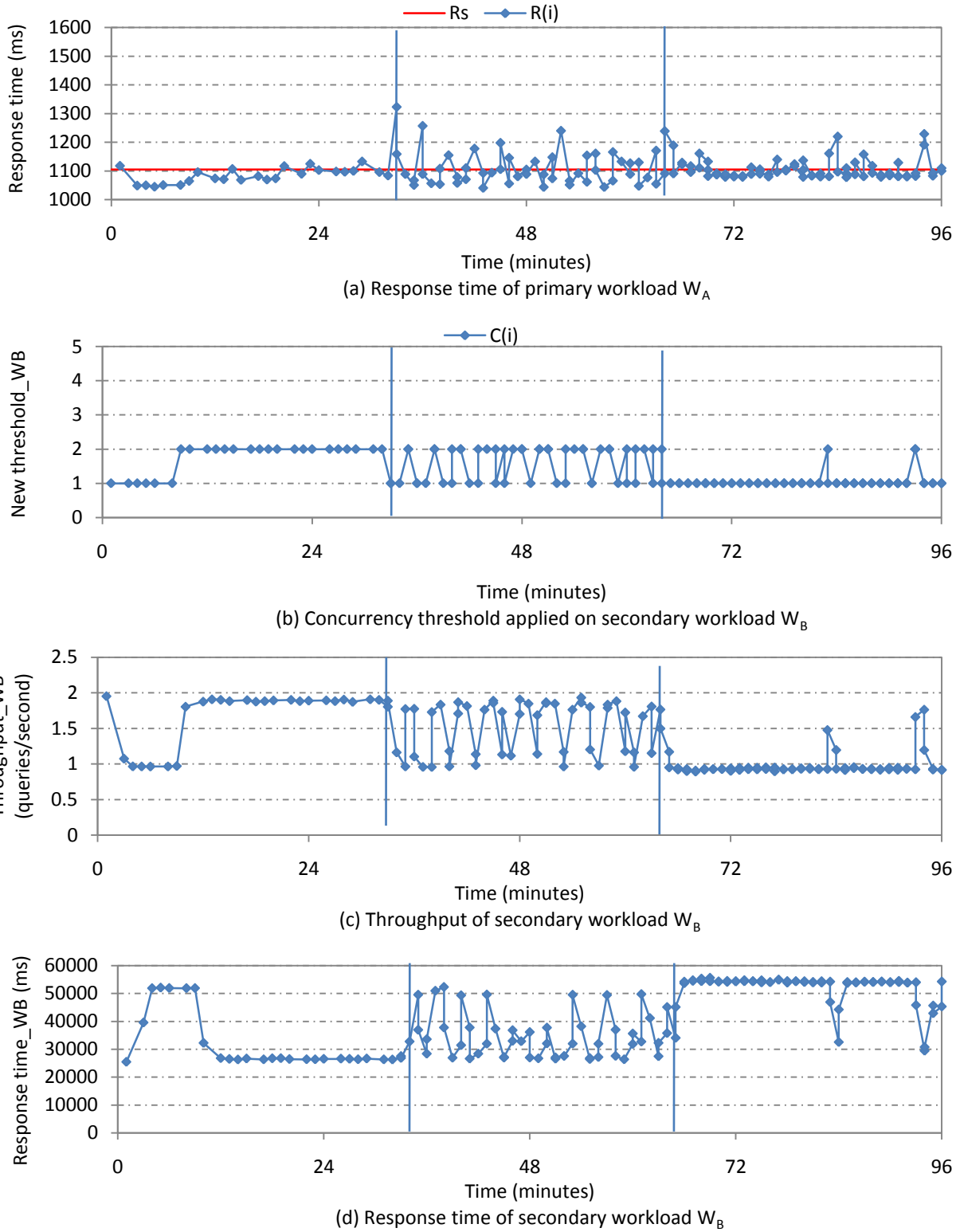



**Figure 12: Controller experiment results with inputs: $R_S$ = 1105ms, $K_I$ = 0.01/6, I = 20**

### 4.7.2 Controller Experiment 7: Workload decrease

In this experiment, we repeat Controller Experiment 6, but in the reverse direction. The workload on the system is decreased by a large magnitude after every 1/3rd of the experimental runtime. We remove workload stream $W_C$ from the primary workload $W_A$ after every 32 minutes into the experiment. Therefore, the workloads in the three phases of the experiment are shown in Table 6.

| Phase | Primary workload | Secondary workload |
|---|---|---|
| 1 | $W_A+W_C+W_C+W_C$ | $W_B$ |
| 2 | $W_A+W_C+W_C$ | $W_B$ |
| 3 | $W_A+W_C$ | $W_B$ |

**Table 6: Workloads in each phase of Experiment 7**

The purpose of this experiment is to study how the controller adapts to large workload changes. The challenge in this experiment is that we change from a workload with the response time objective 1105 ms corresponding to a lower threshold value to a workload with the response time objective 1105 ms corresponding to a higher threshold. Therefore, when the workload decreases, we expect the controller output to increase without overshoot and oscillation and then converge onto the right concurrency threshold corresponding to the objective or toggle between two thresholds, between which the objective exists.

We perform this experiment with the same $K_I$ and $I$ values as Controller Experiment 6. We use a controller constant $K_I$ of value 0.01/6 and a control interval $I$ of a minimum of 20 primary workload queries. Figure 13 shows the results of this experiment. In Figure 13(a), in the first phase, the response time objective 1105 ms corresponds to concurrency threshold 1 and therefore, the controller output *C(i)* (in Figure 13(b)) settles on threshold 1. In the second phase, the objective 1105 ms shifts to corresponding to a concurrency threshold value lying in between thresholds 1 and 2 and therefore, *C(i)* oscillates between the thresholds 1 and 2. In the third phase, the objective 1105 ms shifts to corresponding to concurrency threshold 2 and therefore, the controller output settles to

threshold 2. The effect of the shift due to workload changes can be seen in the throughput and the response time graphs of the secondary workload $W_B$ too.

This experiment shows that the controller is able to dynamically adapt to decrease in workload, i.e. decrease in CPU utilization, without any performance problems due to a change in the workload.

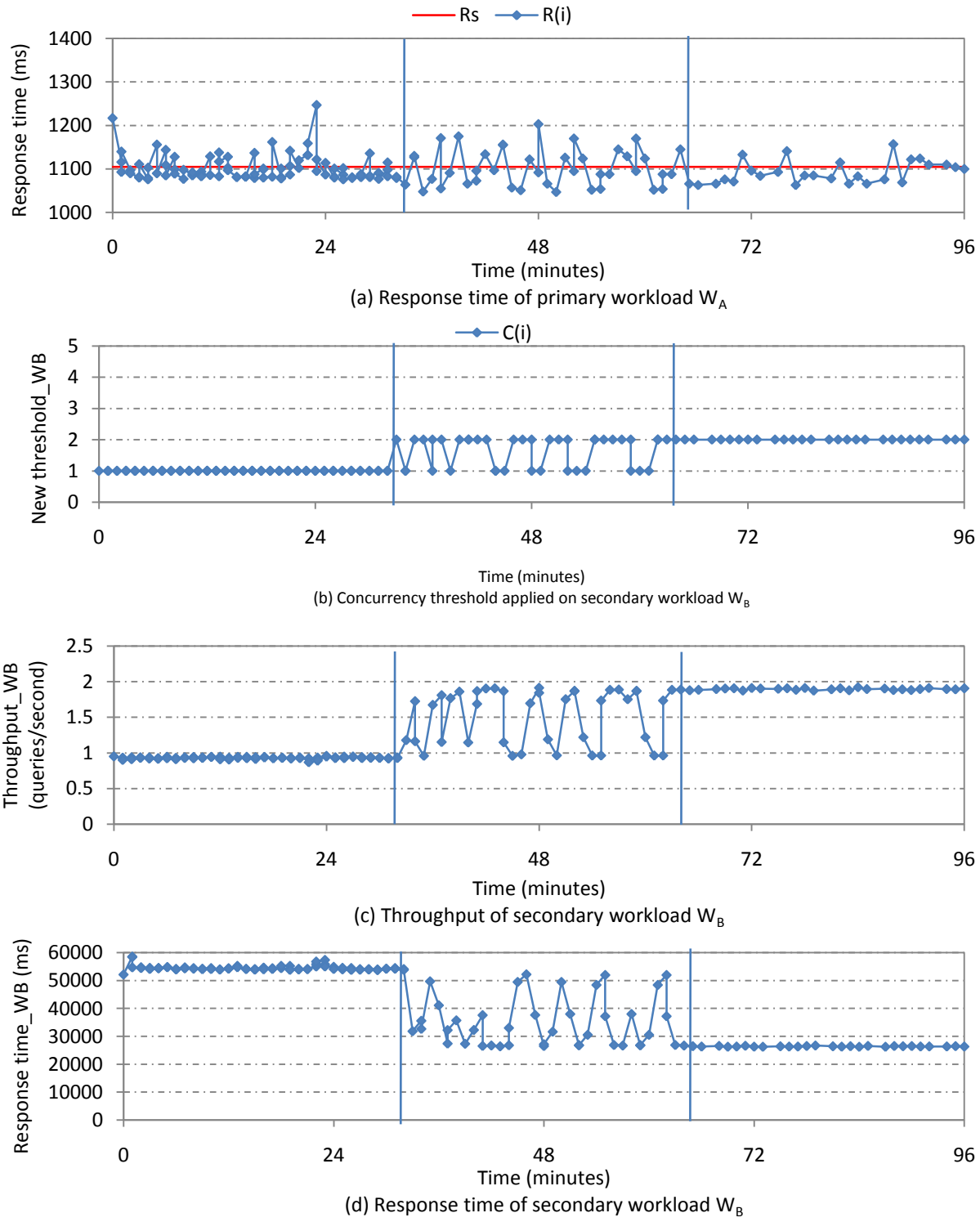



**Figure 13: Controller experiment results with inputs: $R_S$ = 1105ms, $K_I$ = 0.01/6, I = 20**

### 4.7.3 Conclusion

All the experiments in this section show that the controller can dynamically adapt to changes in the workload appropriately. When the workload changes, the controller measures the change through the response time average *R(i)* as the response time average of the primary workload changes due to a change in CPU utilization in the system. This results in error when the controller compares the response time average *R(i)* with the response time objective $R_S$. As a result, the controller makes appropriate changes to the concurrency threshold *C(i)* on the secondary workload, thereby regulating the number of secondary workload queries executing in the system so that response time average *R(i)* of the primary workload is directed towards objective $R_S$. There were no performance problems of overshoot and oscillation due to a change in the workload.

These experiments also show that when a response time objective $R_S$ does not correspond to a concurrency threshold, the controller toggles between two thresholds, between which the objective exists. This results in variant response times for the primary workload without achieving the objective but only keeping the overall response time average over a larger interval at the objective $R_S$. Moreover, the fact that the concurrency threshold on the secondary workload is applied variably, it may not be an attractive behavior of the controller. This shows that the response times of the primary workload cannot be achieved at a finer granularity and therefore, workload control through concurrency threshold is a coarse form of control. However, it is to be noted that the more secondary workload classes there are to control, the more granularity we achieve in controlling the response times of the primary workload.

## 4.8 Controller Parameter Tuning and Discussion

In this section, we present the controller experiments with poorly tuned input parameters, controller constant $K_I$ and control interval $I$. The purpose of these experiments is to show the performance problems involved when the controller constant $K_I$ and control interval $I$ are poorly set for the controller. We then discuss how to go about choosing appropriate values for $K_I$ and $I$ by manual tuning, based on trial and error. We end this section by giving some pointers to cut down manual tuning.

### 4.8.1 Controller Experiment 8: Performance Problem with Small Controller Constant $K_I$

We repeated Controller Experiment 1 (in Section 4.5) with smaller controller constant $K_I$ of value 0.001 instead of 0.01. The purpose of this experiment is to show how the controller performs if $K_I$ is too small. We perform this experiment with a lower $K_I$ of value of 0.001 on response time objective of 1082 ms from the no-CPU-contention environment. As explained earlier, we expect a low $K_I$ of value 0.001 to work, but at the expense of slowing the controller in converging onto the expected concurrency threshold 2.

Figure 14 shows the results of this experiment. The controller output graph (in Figure 14(b)) shows that the controller output *C(i)* reaches the expected threshold 2 in 3000 seconds (75 control steps, each after an interval of 40 seconds), which is nearly 10 times that of Controller Experiment 1. Correspondingly, the response time average *R(i)* (in Figure 14(a)) also reaches the response time objective 1082 ms. The minor oscillations (step-downs) observed in *C(i)* in Experiment 1 are also visibly reduced.

This result shows that if the controller constant $K_I$ is too small, then the controller takes a long time to converge on the response time objective $R_S$. The reason is that if we reduce $K_I$ by 10 times, the controller takes control steps that are 10 times smaller in size. This makes the controller 10 times slower in responding to errors. Hence, the convergence time of the controller is increased by 10 times.

We may increase the convergence time by reducing the control interval *I*. However, with the low arrival rate of the primary workload queries, there can be significant variance in the response time measurements of the primary workload and can result in the performance problem of oscillation, which we will be discussing about in Section 4.8.3.

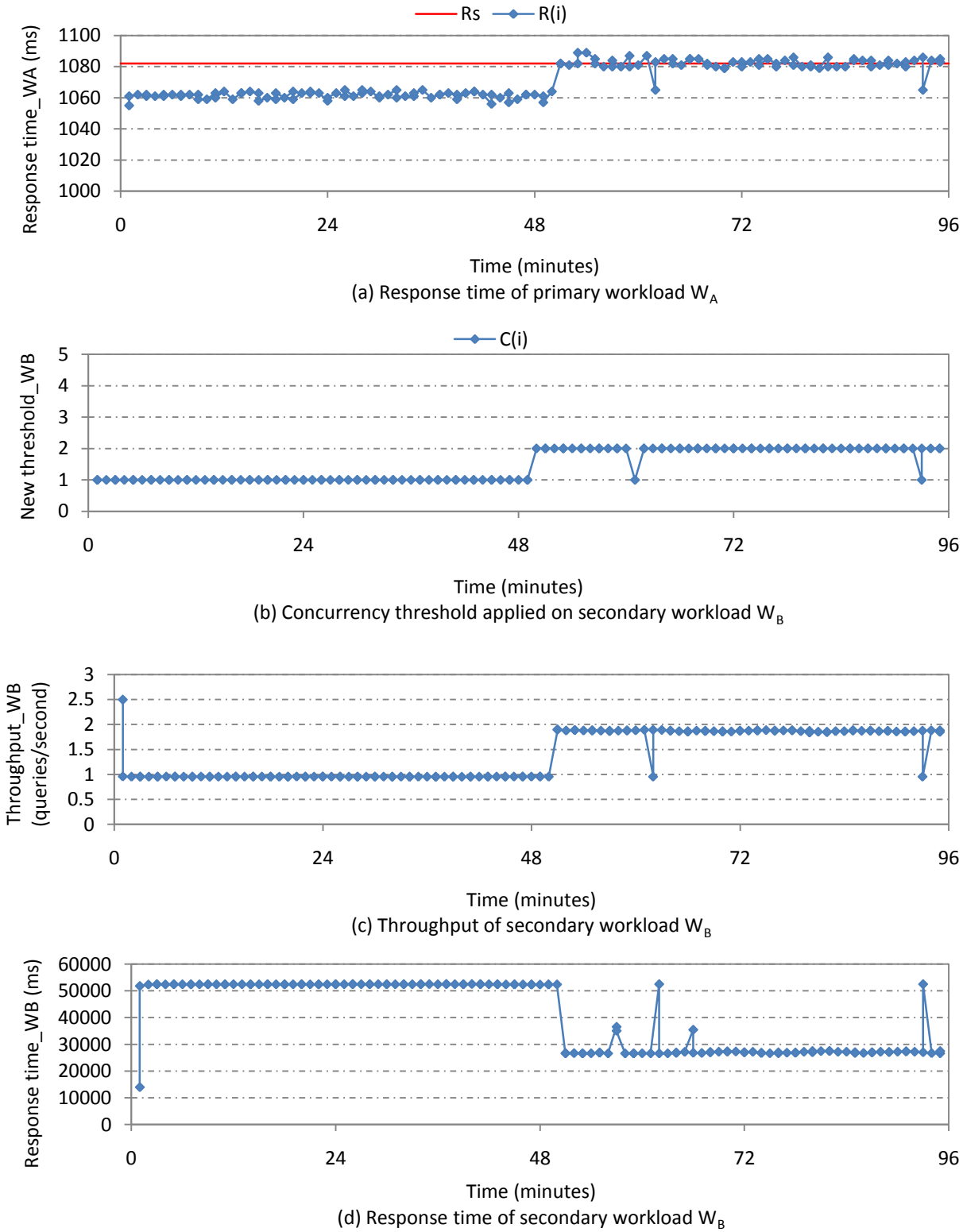


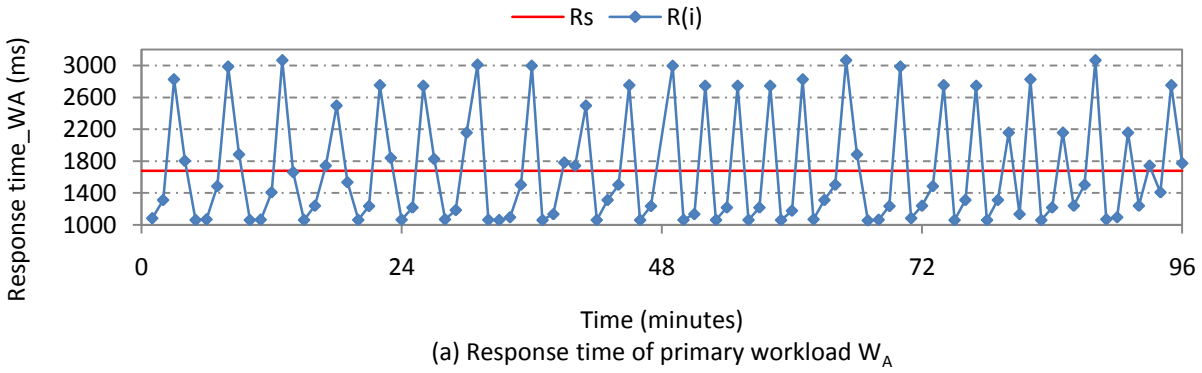

**Figure 14: Controller experiment results with inputs: $R_S$ = 1082ms, $K_I$ = 0.001, I = 20**

### 4.8.2 Controller Experiment 9: Performance Problem with Large Controller Constant $K_I$

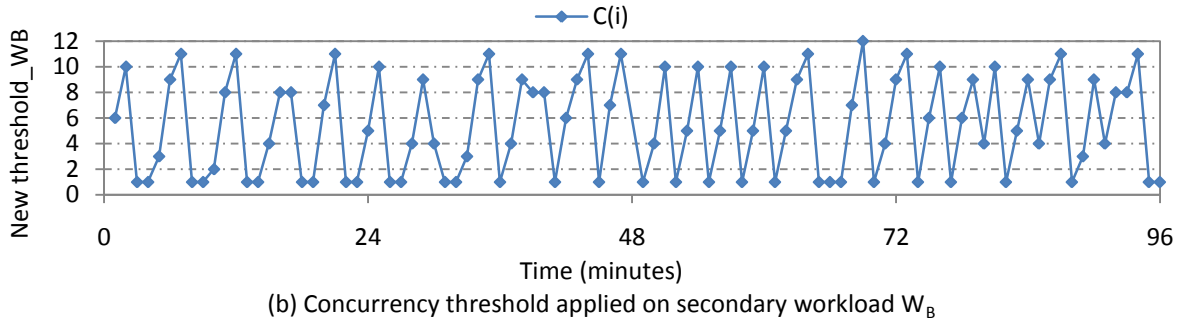
We repeated Controller Experiment 2 (in Section 4.5) with a higher controller constant $K_I$ of value 0.01 instead of 0.001. We perform the experiment with a response time objective of 1682 ms and a control interval of a minimum of 20 primary workload queries. The purpose of this experiment is to show how the controller performs if $K_I$ is too big.

Figure 15 shows the results of this experiment. The controller output graph (in Figure 14(b)) shows that the controller output *C(i)* overshoots the expected concurrency threshold 4 and oscillates without converging onto the expected threshold. Correspondingly, the same is observed in the response time average *R(i)* graph of the primary workload where *R(i)* overshoots the objective and oscillates.

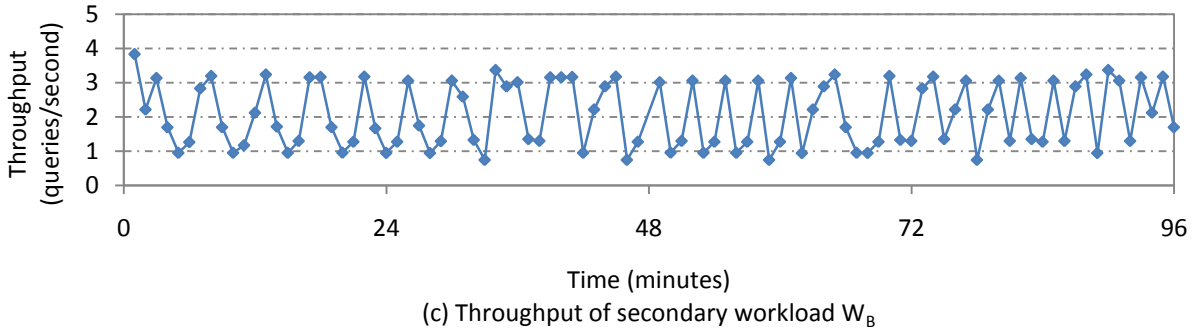
This result shows that if the controller constant $K_I$ is too big, then the controller overshoots the response time objective $R_S$ and oscillates without nearing the objective $R_S$. The reason is that if we increase $K_I$ value by 10 times, the controller takes control steps that are 10 times larger in size when compared to Controller Experiment 2. This makes the controller 10 times more aggressive in responding to errors.



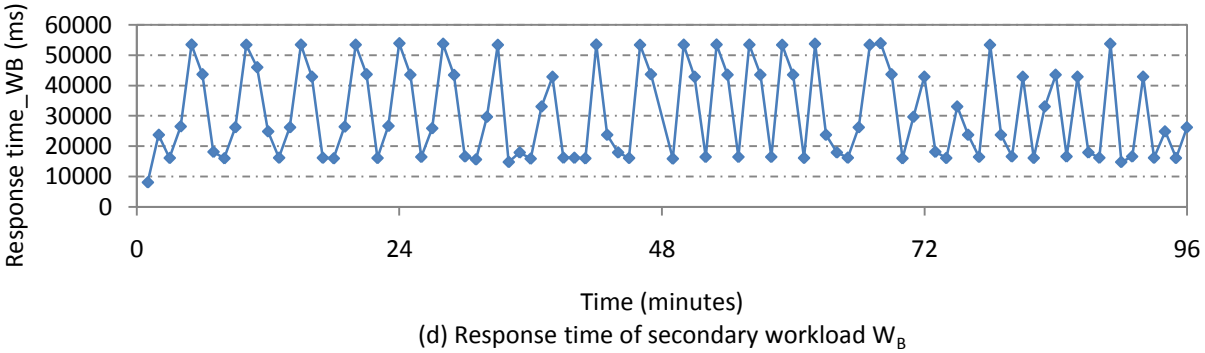

(a) Response time of primary workload $W_A$




(b) Concurrency threshold applied on secondary workload $W_B$




(c) Throughput of secondary workload $W_B$




(d) Response time of secondary workload $W_B$

**Figure 15: Controller experiment results with inputs: $R_S$ = 1682ms, $K_I$ = 0.01, I = 20**

### 4.8.3 Controller Experiment 10: Performance Problem with improper Control Interval I

We repeat Controller Experiment 2 (in Section 4.5) with a smaller control interval *I* of a minimum of 20 primary workload queries instead of a minimum of 40 primary workload queries. We perform the experiment with a response time objective of 1682 ms and a controller constant $K_I$ of 0.001. The purpose of this experiment is to show how the input parameter *I* affects the performance of the controller.

Figure 16 shows the results of this experiment. The new threshold graph (Figure 16(b)) shows that the controller output *C(i)* smoothly climbs to the expected concurrency threshold 4 in 280 seconds (7 control steps, each after an interval of 40 seconds), which is half of that of Controller Experiment 2, but oscillates largely between concurrency thresholds 3 and 4 and does not stabilize on threshold 4. This is due to high variance in the response time measurements at threshold 4.

This result shows that the number of primary workload queries in a control interval *I* affect the performance of the controller. Provided with a proper controller constant $K_I$, the controller output *C(i)* reaches the expected concurrency threshold without overshoot, but oscillates around the expected threshold and does not settle on the threshold. The reason is for this is that if there are fewer queries in a control interval *I*, the controller is more prone to being affected by the variance in the response time average measurements. Having more primary workload queries in a control interval *I* smoothes out the variance as the response time average measurements is averaged over more queries.

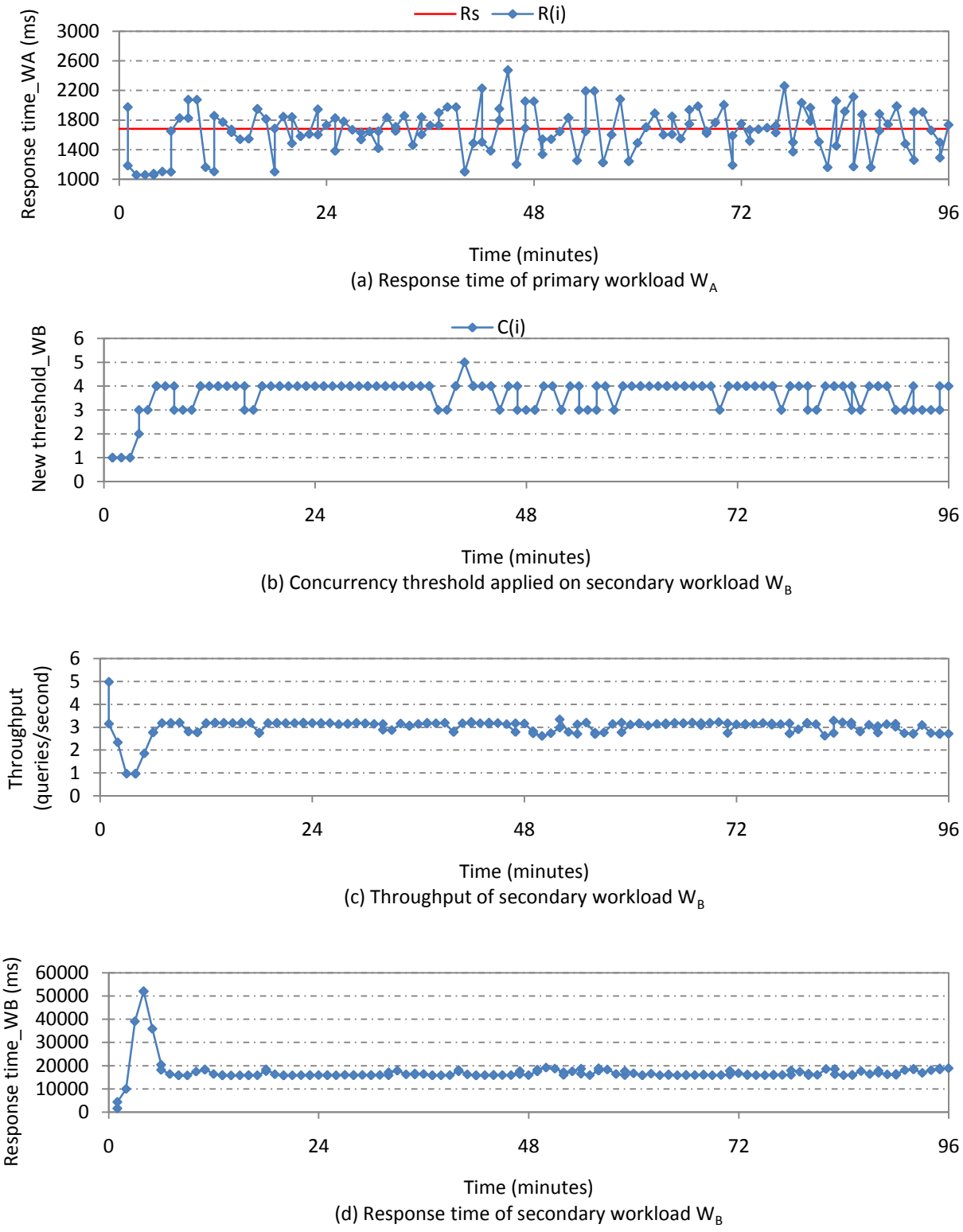



**Figure 16: Controller experiment results with inputs: $R_S$ = 1682ms, $K_I$ = 0.001, I = 20**

### 4.8.4 Tuning Controller Constant $K_I$ and Control Interval I Experimentally

Inappropriate values for $K_I$ and $I$ can result in performance problems of overshoot, oscillation and longer convergence times. Therefore, proper tuning is necessary for $K_I$ and $I$.

By tuning the parameters $K_I$ and $I$, we are able to control the aggressiveness of the controller. Tuning $K_I$ changes the size of the control steps taken by the controller to move from one threshold to another and therefore, by tuning $K_I$, we are able to control the controller's sensitivity to error. Tuning $I$ changes the number of control decisions per unit time, thereby changing the time span over which the response time measurements of the primary workload are averaged and therefore, by tuning $I$, we are able to control the controller's sensitivity to variance.

The following is how to deal with a performance problem of overshoot and oscillation by tuning $K_I$ and $I$.

1. If the controller overshoots the response time objective $R_S$, oscillates and does not near the objective, as in Controller Experiment 9, then this problem is due to a high $K_I$ and therefore, $K_I$ needs to be decreased.
2. If the controller converges onto the objective $R_S$ but doesn't stay on $R_S$ and oscillates, as in Controller Experiment 10, then this problem is due to significant variance in the response time measurements of the primary workload and therefore, $I$ needs to be increased to minimize variance.

The performance problem of longer convergence time, where the controller takes a significant amount of time to converge onto the objective $R_S$, as in Controller Experiment 8, is due to a low $K_I$ and therefore, $K_I$ needs to be increased. It is to be noted that decreasing $I$ can also increase the convergence time.

### 4.8.5 Choosing Controller Constant $K_I$

In all the controller experiments in this thesis, we used values for controller constant $K_I$ that were obtained experimentally, based on trial and error. We used a $K_I$ of value 0.01 for response time objectives from the no-CPU-contention environment and a $K_I$ of value 0.001 for response time objectives from the CPU-contention environment. Practically, it is not realistic to perform manual

tuning of $K_I$ without having any pointers to starts from. Therefore, we discuss some possible ways to reduce manual tuning in this section.

In the previous chapter, we defined the controller constant $K_I$ to be the amount by which the controller should manipulate the concurrency threshold for a unit amount of error in the response time of the primary workload.

$$K_I = \frac{C(i) - C(i-1)}{E(i)}$$

Considering the slopes of trends from the response time curve (in Figure 2(a)) in the workload characterization experiment, for response time objectives from the no-CPU-contention environment, we know that we want the controller to have the granularity to change the concurrency threshold at most by 1 if the error is of value 23 ms. Therefore, we want $K_I$ of value 0.04 in no-CPU-contention environment.

$$K_I = \frac{1}{23} = 0.04$$

Similarly, for response time objectives from the CPU-contention environment, we know that we the controller to change the concurrency threshold by 1 if the error is of value 225 ms. Therefore, we want $K_I$ of value 0.004 in CPU-contention environment.

$$K_I = \frac{1}{225} = 0.004$$

These values 0.04 and 0.004 for $K_I$ are the highest that $K_I$ should be in each environment, making the controller to adjust for response time error in a single control step, which may result in an aggressive controller.

From the properly tuned controller experiments in Section 4.5, Controller Experiment 1 took 6 control steps to move from threshold 1 to threshold 2 in the beginning of the experiment in no-CPU-contention environment. Therefore, the $K_I$ value that works well in that experiment should be 0.0067.

$$K_I = \frac{0.04}{6} = 0.0067$$

When this value is rounded off, it is equal to 0.01, which is what we used in Controller Experiment 1.

Similarly, Controller Experiment 2 took 3 control steps to move from threshold 3 to threshold 4 in the beginning of the experiment in CPU-contention environment. Therefore, the $K_I$ value that works well in that experiment should be 0.0013.

$$K_I = \frac{0.004}{3} = 0.0013$$

When this value is rounded off, it is equal to 0.001, which is what we used in Controller Experiment 2.

Hence, the values 0.01 and 0.001 for the controller constant $K_I$ that we used, though arrived at experimentally, are consistent with the slopes of the response time curve (in Figure 6(a)) in the workload characterization experiment.

**Model to suggest controller constant $K_I$**

Practically, in order to decide how to set the controller constant $K_I$ in a real system, it may not be possible for the system administrator to perform the workload characterization to get the slope of the response time curve (in Figure 2(a)) of the primary workload. However, the following model can be used to suggest a reasonable $K_I$ value to start with, which can be tuned later on as per the performance of the controller.

In this section, we present a model that suggests a reasonable controller constant $K_I$ value to start with, which can be tuned as per the performance of the controller. We use the response time $R$ of a single query of the primary workload and the number of processors $P$ in the system to estimate the response time of the primary workload when $C_{total}$ concurrent queries are running in the system. If the administrator does not know the response time $R$, then a calibration run can be done in which the primary workload is run alone in isolation. The response time average calculated from this run can be used as the response time $R$. If $R(C_{total})$ represents the response time of the primary workloads with $C_{total}$ number of concurrent queries (of all workloads) running in the system, then the following can be used to estimate $R_{Ctotal}$.

$$R(C_{total}) = \begin{cases} R\ ,\ C_{total} \leq P \\ \frac{C_{total}}{P} R,\ C_{total} > P \end{cases}$$

In other words, as long there are at most $P$ concurrent queries running in the system, the response time of a query does not increase. If the number of concurrent queries running in the system goes above $P$, then the response time of a query increases linearly with the number of concurrent queries.

For simplicity, we consider only the case in which $C_{total} > P$. The slope of $R(C_{total})$ is the relationship between the response time and the number of concurrent queries. The slope is $\frac{R}{P}$ time units per query. As explained in the previous chapter, controller constant $K_I$ needs to be queries per unit time. Therefore, the value that we want for $K_I$ is the inverse of the slope of $R(C_{total})$.

$$K_I = \frac{P}{R}$$

This $K_I$ value obtained from the inverse of the slope of $R(C_{total})$ will result in the controller taking large control steps and trying to correct response time error in a single control step, which may result in an aggressive controller. Therefore, this $K_I$ value should be divided by the number of control steps the controller should take before correcting the error entirely. Therefore, if $n$ is an arbitrary number of control steps chosen by the administrator,

$$K_I = \frac{P}{R * n}$$

In our system, $P = 4$ and for our primary workload, $R$ = 1000 ms. Since we are considering only the condition where $C_{total} > P$, we are looking at the CPU-contention environment from our controller experiments. In our controller experiments, there were 3 control steps in the CPU-contention environment. Therefore, if we consider 3 control steps,

$$K_I = \frac{4}{1000 * 3} = 0.0013$$

When this value is rounded off, it is equal to 0.001. This $K_I$ of value 0.001 is the same as what we had used for most of our controller experiments that worked well. Hence, this validates our model.

In summary, given the response time $R$ of a query of the primary workload and the number of processors $P$ in the system, this model can suggest a reasonable value for $K_I$ for the administrator to start with. This suggested $K_I$ value is best when $C_{total} > P$. For $C_{total} \leq P$, there still needs to be some tuning to find out the best $K_I$ value, but at least the administrator knows that the value is bigger than the $K_I$ value derived from the model because the slope of $R(C_{total})$ will be small. Therefore, though this model suggests a $K_I$ value to reduce a lot of manual tuning, there still needs to be some

tuning required to find the best controller constant $K_I$, which can be done experimentally based on the guidelines presented in Section 4.8.4.

### 4.8.6 Choosing Control interval I

In all the controller experiments, we used arbitrary values for the control interval *I*. We had to consider variance in tuning the control interval *I* because the workloads that we used had a low arrival rate of queries. In the no-CPU-contention environment, the variance in the response time measurements was less and hence, we used a smaller control interval of a minimum of 20 primary workload queries. In the CPU-contention environment, the variance in the response time measurements was significantly high and in order to smooth out the variance, we used a longer control interval *I* of a minimum of 40 primary workload queries.

Practically, the control interval *I* may not require a lot of tuning because most of the transactional database workloads in a real system have high arrival rates. Hence, a reasonable control interval can be easily chosen by the system administrator and the interval will have a good number of queries and therefore there will not be any significant variance in the response time average measurements. The same control interval will work for both no-CPU-contention environment and CPU-contention environment. We examine the feasibility of using our controller on workloads with higher arrival rates in the next section.

## 4.9 Workloads with Small Inter-Arrival Time and Small Service Time

Most of the transactional workloads in current DBMSs have a high arrival rate of queries with sub-second service times. Therefore, we examine the feasibility of achieving response time objectives for workloads with small service time $T_S$ and small inter-arrival time $T_A$.

### 4.9.1 Effectiveness of Controller on Workloads with Higher Arrival Rate

We use two workload streams $W_D$ and $W_E$ as shown in Table 7. We use a service time of 200 ms and an inter-arrival time of 120 ms for the primary workload $W_D$ and the secondary workload $W_E$.

Therefore, both the workloads together have a CPU utilization of 3.2. We use random service time $T_S$ and random inter-arrival time $T_A$.

| Test Workloads | Workload Streams | $T_S$ [value (ms), distribution] | $T_A$ [value (ms), distribution] |
|---|---|---|---|
| Primary | $W_D$ | 200, exponential | 120, exponential |
| Secondary | $W_E$ | 200, exponential | 120, exponential |

**Table 7: Test workloads $W_D$ and $W_E$ configurations**

We perform workload characterization as in Experiment 2 of Section 5.4 on workloads $W_D$ and $W_E$. In this experiment, we determine whether admission control on the secondary workload $W_E$ is an effective way to control the response time of the primary workload $W_D$. The result of the experiment is shown in Figure 16.

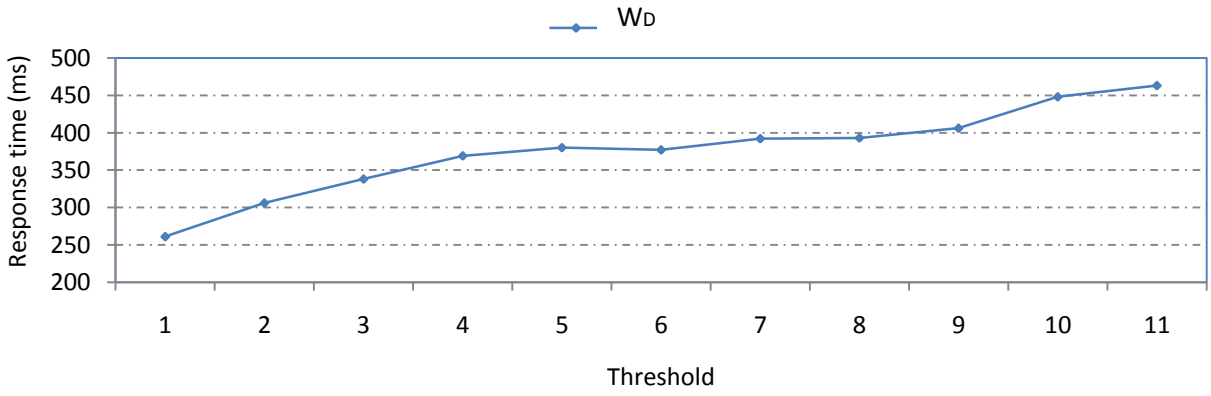



**Figure 17: Sensitivity of response time average of $W_D$ to concurrency threshold on $W_E$**

The figure shows that the response time averages of $W_D$ increase consistently, starting from threshold 1. This is because of increase CPU utilization with increase in concurrency threshold on $W_E$. With exponential service times and exponential inter-arrival times, there may be queries with service

times that are much longer than 200 ms and inter-arrival times that are much smaller than 120 ms. This keeps the system sufficiently overloaded, creating our problem scenario.

Therefore, with the response time averages of the primary workload $W_D$ consistently increasing and with a high arrival rate of the queries in $W_D$, our controller should be effective on these workloads. Hence, the controller can work with a controller constant $K_I$, which can be derived from our model for $K_I$ as explained in Section 4.8.5, and a reasonable control interval $I$. $K_I$ can be tuned later on, if required, according to the performance of the controller.

### 4.9.2 Effectiveness of Controller on Workloads with Small Service Time

We repeat workload characterization as in Experiment 2 with two workload streams $W_F$ and $W_G$ with small, deterministic service times. The workload configurations are shown in Table 8. The workloads $W_F$ and $W_G$ are workloads $W_A$ and $W_B$ but scaled down to $1/10^{th}$ of their service times and inter-arrival times. We use a service time of 100 ms and an inter-arrival time of 200 ms for the primary workload $W_D$. We use a service time of 100 ms and an inter-arrival time of 30 ms for the secondary workload $W_E$. Therefore, both the workloads together have a CPU utilization of 3.83. The purpose of using these workloads is to particularly see the feasibility of admission control on queries with small, sub-second service times. The results are shown in Figure 18.

| **Test Workloads** | **Workload Streams** | $T_S$ **[value (ms), distribution]** | $T_A$ **[value (ms), distribution]** |
|---|---|---|---|
| Primary | $W_F$ | 100, deterministic | 200, deterministic |
| Secondary | $W_G$ | 100, deterministic | 30, exponential |

**Table 8: Test workloads $W_F$ and $W_G$ configurations**

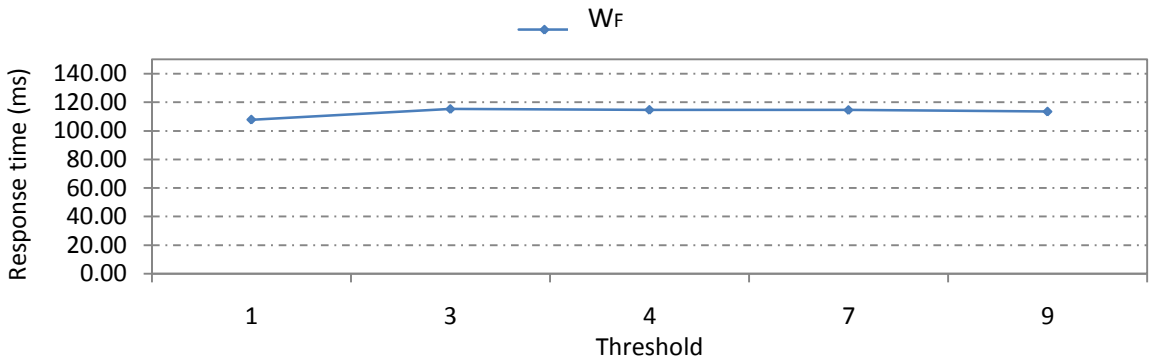



**Figure 18: Sensitivity of response time average of $W_F$ to concurrency threshold values on $W_G$**

The figure shows that the response time averages of $W_F$ are not affected by change in concurrency threshold on $W_G$. This is because the queries of the workloads are too short, probably shorter than the CPU time slice of the operating system's scheduler. If we assume that the operating system uses round robin (RR) scheduling, with the time slice being too big for the very small queries, the RR scheduler will start to perform as a first-come-first-serve (FCFS) scheduler. Therefore, the context switches for each query becomes significantly low. Therefore, with increase in concurrency, there is negligible increase in context switches for each query and therefore, CPU wait time $T_W$ for each query will almost remain the same. In conclusion, the response times of these very small queries do not increase by increase in the number of concurrent queries in the system. This proves that our controller's concurrency threshold control will not be effective for workloads with very small queries.

## 4.10 Summary

In this chapter, based on all the experiments, we can conclude that our admission controller has a certain number of advantages and a certain number of disadvantages.

The following are the advantages of the controller:

1. The controller is able to keep the response time average of the primary workload at the response time objective with minimal performance problems, after careful tuning of input parameters: controller constant $K_I$ and control interval $I$.

2. The controller, if properly tuned, is able to automatically adjust to changing response time objective and changing workload conditions without any performance problems.
3. The aggressiveness and the convergence time of the controller can be controlled by controlling the controller constant $K_I$ and the control interval $I$.

The following are the disadvantages of the controller:

1. Tuning the controller constant $K_I$ and the control interval $I$ may be difficult in practice.
2. If the number of secondary workload classes to control is less, the controller's admission control can be a coarse form of control to achieve response time objectives.
3. The controller is not effective for workloads with very small queries because their CPU wait time $T_W$ is not affected by concurrency threshold. Hence, the controller's admission control does not affect the response times of very small queries.

# Chapter 5
# Conclusion

In this thesis, we study achieving performance objectives for a primary workload in DBMSs. We focus on how to use feedback-based admission differentiation to achieve the performance objectives. We use admission control on secondary workloads to achieve objectives for the primary workload. The amount of admission control to be applied is decided on the current performance of the primary workload and how far it is from the objective.

We propose a general architectural framework for feedback-based admission differentiation. It consists of three components: workload classifier, workload monitor and adaptive admission controller. The workload classifier identifies and groups the incoming queries into workloads according to their source or type. The workload monitor is concerned with providing feedback about the workloads to the adaptive admission controller by continuously collecting performance information. The adaptive admission controller calculates and implements admission control on the secondary workload. The adaptive admission controller has two sub-components, namely an advisor and effector. The advisor reads the performance information of the primary workload, compares the information to the workload's objective and calculates the amount of admission control to be applied on the secondary workload. The amount of admission control to be applied is determined by using fundamentals from control theory. Effector implements the admission control calculated on the secondary workload.

In order to prove the effectiveness of feedback-based admission differentiation, we implemented all the components in a commercial DBMS, DB2. We achieve response time objectives for the primary workload by applying admission control in the form of applying a concurrency threshold to the secondary workload.

We show that the adaptive admission controller is able to regulate the response time average of the primary workload towards the workload's response time objective by controlling the concurrency threshold on the secondary workload, given an appropriate controller constant $K_I$ and control interval $I$.

We evaluate the controller in different scenarios in which the response time objective or the workload changes. The experiments in which response time objective changes show that the controller can achieve both the objectives and handle the change effectively without oscillation. The experiments in which workload changes show that the controller can dynamically achieve the objective through the workload changes, without oscillation as well.

We show how controller constant $K_I$ and control interval $I$ affect the performance of the controller. The experiments show that we can control the aggressiveness of the controller by changing $K_I$ and $I$.

We also show the feasibility of the using the controller for workloads with a high arrival rate and sub-second service times. The experiments showed a limitation of the controller that it is not effective on workloads with very small queries because the queries are too small and therefore, the context switching for each query does not increase with increase in concurrency in the system. Therefore, the controller's concurrency threshold control on the secondary workload (with small queries) do not affect the response times of the primary workload (with very small queries).

In conclusion, a properly tuned adaptive admission controller is able to achieve response time objectives for an important, primary workload by applying concurrency threshold control on the less important, secondary workload, as long as the workload do not consist of very small queries. Hence, the controller experiments in this thesis show that it is feasible to use feedback-based admission differentiation to achieve performance objectives for a primary workload in a DBMS.

Having shown the effectiveness of the controller, it will be interesting to see the following as future work:

1. Develop a method to auto-tune the controller constant $K_I$. In this thesis, we showed a model to derive a value for controller constant $K_I$ with the response time $R$ and the number of processors $P$. Though the derived value saves the administrator from a lot of tuning, it may still require a bit of tuning to obtain the best $K_I$ value. Hence, it is necessary to develop a well-defined process to tune $K_I$ automatically to avoid any manual tuning.

2. Enhance our feedback-based admission differentiation framework to achieve per-class performance objectives for multiple workload classes. Achieving multiple performance objectives is complicated by the interdependence between workload classes. Achieving performance objective of one class affects the performance of the other classes. Therefore, we

need to develop a well-defined function to manage the objectives of all the workload classes collectively.

3. Improve the objective specification for the architectural framework to include business importance of the workload classes. In this thesis, we assumed the business importance of the workloads and we designed the architectural framework to allow specifying the performance objectives as values. There is no method to specify business importance of a workload class which can define how important it is to achieve the objective of the class relative to other workload classes. Therefore, integrating importance of workload classes along with their performance objectives will be a good improvement to add to the framework.
4. Test the controller for achieving performance objectives of other metrics. For example, if applying concurrency threshold on the secondary workloads affects the throughput of the primary workload, then the controller can achieve throughput objectives of the primary workload.
5. Investigate if the controller can be used on a wider range of workloads and not just read-only transactional workloads.

# References


[1] IBM Canada. Introduction to DB2 9.5 Workload Management. 2007.

[2] J. L. Hellerstein, Y. Diao, S. Parekh and D. M. Tilbury. Feedback Control of Computing Systems. John Wiley & Sons, 2004.

[3] S. Krompass, A. Scholz, M. Albutiu, H. Kuno, J. Wiener, U. Dayal and A. Kemper. Quality of Service-Enabled Management of Database Workloads. *IEEE Data Engineering Bulletin, Special Issue on Testing and Tuning of Database Systems,* volume 31, issue 1, 2008.

[4] A. Moenkeberg and G. Weikum. Conflict-driven load control for the avoidance of data-contention thrashing. In *Proceedings of the Seventh International Conference on Data Engineering,* pages 632-639, 1991.

[5] M. J. Carey, S. Krishnamurthi and M. Livny. Load control for locking: The "half-and-half" approach. In *PODS '90: Proceedings of the Ninth ACM SIGACT-SIGMOD-SIGART Symposium on Principles of Database Systems,* Nashville, Tennessee, United States, pages 72-84, 1990.

[6] H. Heiss and R. Wagner. Adaptive load control in transaction processing systems. In *VLDB '91: Proceedings of the 17th International Conference on very Large Data Bases,* pages 47-54, 1991.

[7] K.D. Kang, Sang H. Son and John A. Stankovic. Service differentiation in real-time main memory databases. In *ISORC '02: Proceedings of the Fifth IEEE International Symposium on Object-Oriented Real-Time Distributed Computing,* page 119, 2002.

[8] S. Elnikety, E. Nahum, J. Tracey and W. Zwaenepoel. A method for transparent admission control and request scheduling in e-commerce web sites. In *WWW '04: Proceedings of the 13th International Conference on World Wide Web,* New York, NY, USA, pages 276-286, 2004.

[9] B. Schroeder, M. Harchol-Balter, A. Iyengar, E. Nahum and A. Wierman. How to determine a good multi-programming level for external scheduling. In *ICDE '06: Proceedings of the 22nd International Conference on Data Engineering,* page 60, 2006.

[10] K. D. Kang, P. H. Sin and D. K. Shin. A feedback-based approach for data contention control. In *Symposium of Information and Communication Technology,* Raleigh, North Carolina, August, 2004.

[11] K. P. Brown, M. Mehta, M. J. Carey and M. Livny. Towards automated performance tuning for complex workloads. In *VLDB '94: Proceedings of the 20th International Conference on very Large Data Bases,* pages 72-84, 1994.

[12] H. Pang, M. J. Carey and M. Livny. Multiclass Query Scheduling in Real-Time Database Systems.*IEEE Trans.on Knowl.and Data Eng.,* volume 7, issue 4, pages 533-551, 1995.

[13] N. Bhatti and R. Friedrich. Web server support for tiered services. *IEEE Network,* volume 13, issue 5, pages 64-71, September/October, 1999.

[14] T. F. Abdelzaher, K. G. Shin and N. Bhatti. Performance Guarantees for Web Server End-Systems: A Control-Theoretical Approach. *IEEE Trans. Parallel Distrib. Syst.*, volume 13, issue 1, pages 80-96, 2002.

[15] Chenyang Lu, John A. Stankovic, Sang H. Son and Gang Tao. Real Time Systems - Feedback Control Real-Time Scheduling: Framework, Modeling, and Algorithms. In *Journal of Real-Time Systems, Special Issue on Control-Theoretical Approaches in Real-Time Computing*, volume 23, issue 1, page 85, 2002.

[16] J. Huang, J. A. Stankovic, K. Ramamritham and D. Towsley. On using priority inheritance in real-time databases. Technical Report, COINS TR 90-121, Department of Computer and Information Science, University of Massachusetts, Amherst, MA, USA, 1990.

[17] J. Almeida, M. Dabu, A. Manikutty and P. Cao. Providing Differentiated Levels of Service in Web Content Hosting. In *Proceedings of the Workshop on Internet Server Performance*, pages 91-102, 1998.

[18] HP. *HP NeoView Workload Management Services Guide*. August, 2007.

[19] Teradata. *Teradata Dynamic Workload Manager User Guide*. September, 2006.

[20] R. Mistry. Microsoft SQL Server 2008 Management and Administration. Carmel, IN, USA: SAMS, 2009.

[21] IBM. *DB2 Workload Manager for Linux, Unix, and Windows*. Riverton, NJ, USA: IBM Corp, 2008.