# Black-Box Performance Control for High-Volume Non-Interactive Systems

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## Abstract

This paper studies performance control for high-volume non-interactive systems, and uses IBM Tivoli Netcool/Impact—a software product in the IT monitoring and management domain—as a concrete example. High-volume non-interactive systems include a large class of applications where requests or processing tasks are generated automatically in high volume by software tools rather than by interactive users, e.g., data stream processing and search engine index update. These systems are becoming increasingly popular and their performance characteristics are radically different from those of typical online Web applications. Most notably, Web applications are response time sensitive, whereas these systems are throughput centric.

This paper presents a performance controller, TCC, for throughput-centric systems. It takes a black-box approach to probe the achievable maximum throughput that does not saturate any bottleneck resource in a distributed system. Experiments show that TCC performs robustly under different system topologies, handles different types of bottleneck resources (e.g., CPU, memory, disk, and network), and is reactive to resource contentions caused by an uncontrolled external program.

## 1 Introduction

Performance control for online interactive Web applications has been a research topic for years, and tremendous progress has been made in that area [2, 10, 23, 28]. By contrast, relatively little attention has been paid to performance control for a large class of increasingly popular applications, where requests or processing tasks are generated automatically in high volume by software tools rather than by interactive users. Many emerging stream processing systems [1] fall into this category, e.g., continuous analysis and distribution of news articles, as in Google Reader [11] and System S [19].

Moreover, almost every high-volume interactive Web application is supported behind the scene by a set of high-volume non-interactive processes, e.g., Web crawling and index update in search engines [7], Web log mining for portal personalization [22], video preprocessing and format conversion in YouTube, and batch conversion of rich-media Web sites for mobile phone users [3].

Beyond the Web domain, examples of high-volume non-interactive systems include IT monitoring and management [15], overnight analysis of retail transaction logs [5], film animation rendering [14], scientific applications [6], sensor networks for habitat monitoring [20], network traffic analysis [26], and video surveillance [8].

The workloads and operating environments of these high-volume non-interactive systems differ radically from those of session-based online Web applications. Most notably, Web applications usually use response time to guide performance control [2, 23, 28], whereas high-volume non-interactive systems are throughput centric and need not guarantee sub-second response time, because there are no interactive users waiting for immediate responses of *individual* requests. Instead, these systems benefit more from high throughput, which helps lower *average* response time and hardware requirements.

This paper studies performance control for high-volume non-interactive systems, and uses IBM Tivoli Netcool/Impact [16]—a software product in the IT monitoring and management domain—as a concrete example.

Today's enterprise IT environments are extremely complex. They often include resources from multiple vendors and platforms. Every hardware, OS, middleware, and application usually comes with its own siloed monitoring and management tool. To provide a holistic view of the entire IT environment while taking into account dependencies between IT components, a federated IT Service Management (ITSM) system may use a core event-processing engine such as Netcool/Impact to drive and integrate various siloed software involved in IT management.

An IT event broadly represents a piece of information that need be processed by the ITSM system. For instance, under normal operations, transaction response time may be collected continuously to determine the service quality. Monitoring tools can also generate events to report problems, e.g., a database is down. When processing an event, the event-processing engine may interact with various third-party programs, e.g., retrieving customer profile from a remote database and invoking an instant messaging server to notify the system administrator if a VIP customer is affected.

When a major IT component (e.g., core router) fails, the rate of IT events may surge by several orders of magnitude due to the domino effect of the failure. If the event-processing engine tries to process all events concurrently, either the engine itself or some third-party programs working with the engine may become severely overloaded and suffer from thrashing. In this work, the purpose of performance control is to dynamically adjust the concurrency level in the event-processing engine so as to maximize throughput while avoiding fully saturating either the engine itself or any third-party program working with the engine, i.e., targeting 85-95% resource utilization (as opposed to 100%) even during peak usage.

The main difficulty in achieving this goal is caused by the diversity and proprietary nature of the multi-vendor components used in a federated ITSM system. For practical reasons, we can only take a black-box approach and cannot rely on many assumptions presumed by existing performance control algorithms.

- We cannot aggressively maximize performance without considering resource contention with external programs not under our control. Therefore, we cannot use greedy parameter search [25].
- We cannot assume a priori knowledge of system topology (e.g., three-tier), and hence cannot use solutions based on static queueing models [23].
- We cannot assume knowledge of every external program's service-level objectives (as in [18]), or knowledge of every component's performance characteristics, e.g., through offline profiling as in [24]. Therefore, we cannot directly adopt these methods based on classical control theory.
- We cannot assume the ability to track resource consumption of every component, or a prior knowledge of the location or type of the bottleneck. Therefore, we cannot adopt solutions that adjust program behavior based on measured resource utilization level.
- We have no simple performance indicators to guide tuning, such as packet loss in TCP [17] or response time violation in interactive Web applications [2].

## 1.1 Throughput-guided Concurrency Control

The discussion below assumes that the number of worker threads in the event-processing engine controls the concurrency level. We explore the relationship between throughput and the event-processing concurrency level to guide performance tuning (see Figure 1). With too few threads, the throughput is low while system resources are underutilized. As the number of threads increases, the throughput initially increases almost linearly, and then gradually flattens, because the bottleneck resource is near saturation. Once the bottleneck saturates, adding more threads actually decreases throughput because of the overhead in managing resource contention. Finally, using an excessive number of threads causes thrashing, and the throughput drops sharply.

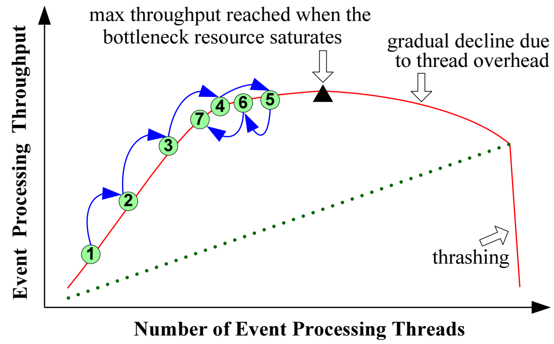



Figure 1: Basic idea of throughput-guided concurrency control (TCC). The symbols ①-⑦ show the controller's operation sequence. If memory is the bottleneck resource, the throughput may follow the dotted line and then suddenly move into thrashing without a gradual transition. This figure is further explained in Section 3.1.

We refer to our controller as **TCC** (throughput-guided concurrency control). Intuitively, it works as follows. Starting from an initial configuration, it tentatively adds some threads (transition ①→② in Figure 1), and then compares the throughput measured before and after the change. If the throughput increases "significantly", it keeps adding threads (transitions ②→③→④), until either the throughput starts to decline or the improvement in throughput becomes marginal (transition ④→⑤). It then successively removes threads (transitions ⑤→⑥→⑦), until the throughput becomes a certain fraction (e.g., 95%) of the maximum throughput achieved during the exploration. The purpose is to reach a stable state that delivers high throughput while not saturating the bottleneck resource.

We address several challenges to make this basic idea practical. Because the exact shape of the thread-throughput curve in Figure 1 varies in different environments, a robust method is needed to determine when the throughput "almost" flattens. If the controller adds threads too aggressively, it may cause resource saturation and gain unfair advantages when competing with an uncontrolled external program. Another challenge is to make quick control decisions based on noisy performance measurement data, e.g., abnormal long pauses caused by Java garbage collection. Our solutions to these challenges are described in Section 3.

Our controller is flexible. It takes a black-box approach to maximize throughput while trying to avoid saturating the bottleneck resource. It makes few assumptions about the operating environment. It need not know system topology, performance characteristics of external programs, resource utilization level, or exactly which resource is the bottleneck. It can handle both hardware (e.g., CPU, memory, disk, or network) and software (e.g.,

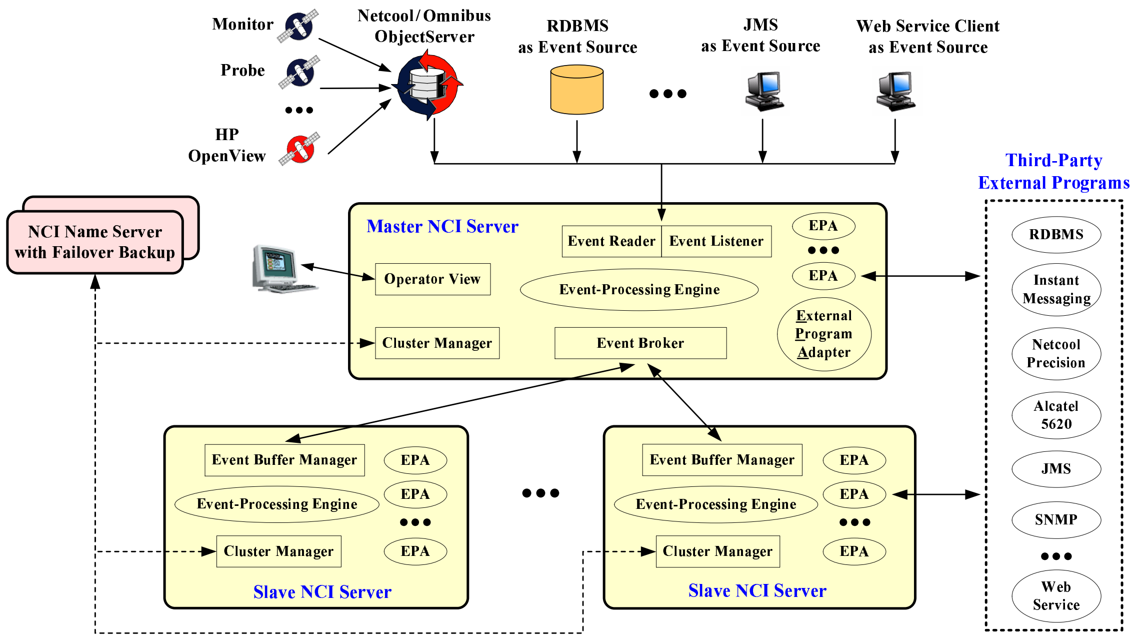



Figure 2: A radically simplified architecture diagram of Netcool/Impact (NCI). IT events flow from top to bottom.

database connection pool) bottleneck resources. Because of its flexibility, it may be broadly applied to high-volume non-interactive systems [1, 6, 7, 19, 20, 22, 26].

We have implemented TCC and integrated it with IBM Tivoli Netcool/Impact [16]. The Netcool suite [15] is a set of software products that help implement a federated ITSM system, and Netcool/Impact is the streaming event-processing engine of the Netcool suite. Experiments demonstrate that TCC performs robustly under different system topologies, handles different types of bottleneck resources, and is reactive to resource contentions caused by an uncontrolled external program.

The remainder of the paper is organized as follows. Section 2 provides an overview of Netcool/Impact. Sections 3 and 4 present and evaluate TCC, respectively. Related work is discussed in Section 5. Section 6 concludes the paper.

## 2 Overview of Netcool/Impact (NCI)

Our performance controller is generic, and its current implementation can actually be configured to compile and run independent of the Netcool/Impact product. To make the discussion more concrete, however, we choose to present it in the context of Netcool/Impact. Netcool/Impact is a mature product with a large set of features. Below, we briefly summarize those features most relevant to our discussion. We simply refer to Netcool/Impact as NCI.

NCI adopts a clustering architecture (see Figure 2). The "master NCI server" is the data fetcher and load balancer. Its "event reader" pulls IT events from various sources, while its "event listener" receives events pushed from various sources. It processes some events in its local "event-processing engine", and dispatches the rest to the "slave NCI servers" for load balancing. The "NCI name server" manages members of the cluster. If the master fails, a slave will be converted into master.

The "event-processing engine" executes user-supplied programs written in the Impact Policy Language (IPL). IPL is a proprietary scripting language specially designed for event processing, emphasizing ease of use for system administrators. With the help of various built-in "external program adapters", IPL scripts can easily integrate with many third-party programs.

Each NCI server (master or slave) uses a pool of threads to process events and runs a performance controller to determine for itself the appropriate thread pool size. When an event arrives, the NCI server goes through a list of admin-specified matching rules to identify the IPL script that will be used to process the event. The event waits in a queue until an event-processing thread becomes available, and then the thread is dispatched to interpret the IPL script with the event as input.

In a large IT environment, monitoring events (e.g., CPU utilization reports) are generated continuously at a high rate even under normal operations. Some events are filtered locally, while the rest are collected in realtime, e.g., to the Netcool/OMNIbus ObjectServer [15], which buffers events and feeds them to the master NCI server in batches, e.g., one batch every five seconds. Events are not sent to the master individually for the sake of efficiency. Similarly, a slave NCI server fetches events in batches from the master.

Because events are fetched in batches, an NCI server often holds a large number of unprocessed events. If the server tries to process all of them concurrently, either the server itself or some third-party programs working with the server will become severely overloaded and suffer from thrashing. Moreover, it needs to carefully control the concurrency level of event processing so that it achieves high throughput while sharing resources with a competing program in a friendly manner.

Our performance control goal is to maximize event-processing throughput while avoiding saturating NCI or any third-party program working with NCI. Even during peak usage, the utilization level of the bottleneck resource should be controlled, e.g., between 85% and 95%, instead of 100%. We must avoid saturating the master NCI server because it hosts other services such as "operator view" (see Figure 2), which provides a customizable dashboard for administrators to look into the details of IT events. In addition, we must avoid saturating third-party programs working with NCI, because they may serve clients other than NCI, including interactive users.

In light of today's complex and heterogeneous IT environments, the success of the NCI product to a great extent owes to its common adapter platform that helps integrate various distributed data sources and siloed monitoring and management tools. Because of the diversity and proprietary nature of these third-party external programs working with NCI, we can only take a black-box approach and cannot rely on many assumptions that are presumed by existing performance control algorithms (as those listed in Section 1) .

# 3 Our Performance Control Algorithm

This section presents our controller TCC in detail. We start with a description of TCC's state transition diagram, and then use queuing models to analyze TCC and demonstrate that it can achieve high resource utilization. We then derive the friendly resource sharing conditions for TCC. We also present a statistical method that minimizes measurement samples needed for making control decisions. Finally, we put all the pieces together to guide the selection of TCC's parameters.

## 3.1 State Transition Diagram

TCC operates according to the state-transition diagram in Figure 3. Most of the time, it stays in the "steady" state, using a constant number of threads to process events that continuously arrive in batches. The number of threads is optimal if those threads can drive the bottleneck resource to a high utilization level (e.g., 85-95%) while avoiding fully saturating it.

Periodically, TCC gets out of the steady state to explore whether a better configuration exists. It moves into the "base" state and reduces the number of threads by $w$%, which will serve as the exploration starting point ① in Figure 1. (How to select parameters such as $w$% will be discussed in Section 3.5.) TCC stays in the "base" state for a short period of time to measure the event-processing throughput. It then increases the number of

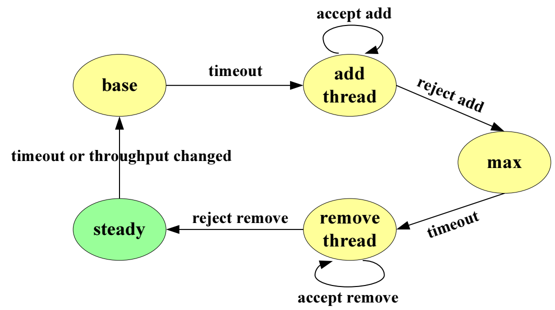



Figure 3: Simplified state-transition diagram of TCC.

threads by $p$% and moves into the "add-thread" state. If this $p$% increase in threads helps improve throughput by $q$% or more, it stays in the add-thread state and repeatedly add threads by $p$% each time. Eventually, the bottleneck resource is near saturation so that a $p$% increase in threads no longer gives a $q$% or more increase in throughput. It then moves into the "max" state.

TCC takes more measurement samples in the "max" state in order to calculate a more accurate baseline throughput. It then moves into the "remove-thread" state to repeatedly removes threads by $r$% each time so long as the throughput does not drop below 95% of the highest throughput achieved during the current tuning cycle.

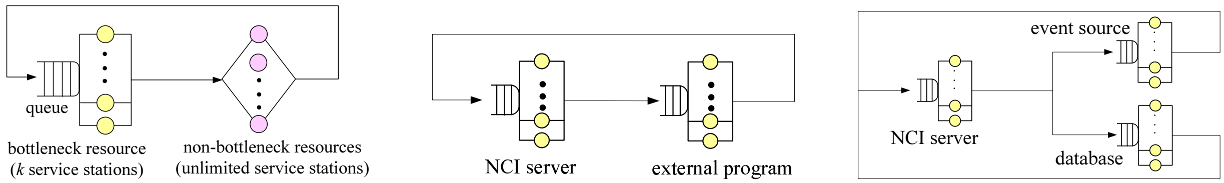
When the throughput finally drops below the 95% threshold, it adds back threads removed in the last round, and moves into the steady state. It stays in the steady state for a relatively long period of time, using an optimal number of threads to process events. It restarts the next round of exploration either after a timeout or when the throughput changes significantly, which indicates a change in the operating environment.

If memory is the bottleneck, throughput may follow the dotted line in Figure 1, and then suddenly moves into thrashing when TCC adds threads. TCC will detect the decline in throughput, revoke the threads just added, and continue to remove more threads until the throughput becomes 95% of the measured maximum throughput. This prevents the system from moving into thrashing.

## 3.2 High Resource Utilization

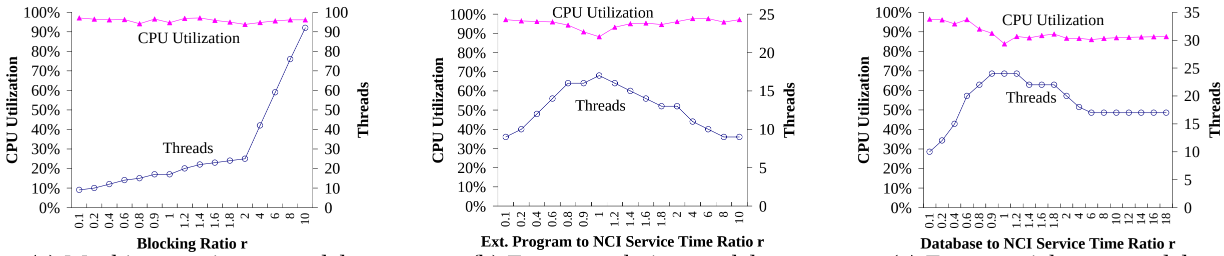
In this section, we use queuing models to demonstrate that, for common event processing scenarios, TCC can achieve high resource utilization (and hence high throughput) while avoiding resource saturation. The discussion below assumes that TCC uses the default configuration: $p$=25%, $q$=14%, and $w$=39%. (Section 3.5 discusses parameter selection.) Our queueing models assume the ITSM system consists of one NCI server and some third-party external programs. We are interested in system behavior when it continuously processes a block of events and we assume no threads remain idle due to the lack of input events.

The first model we use is the machine-repairman model [12] in Figure 4(a). This model assumes that the




(a) Machine-repairman model (b) Event-escalation model (c) Event-enrichment model

Figure 4: Using queueing models to analyze TCC. These closed models can be solved by mean value analysis [12].




(a) Machine-repairman model (b) Event-escalation model (c) Event-enrichment model

Figure 5: Performance of TCC under different queueing models. Note that the $x$-axis increases nonlinearly.

ITSM system has a clearly defined bottleneck resource, whose utilization level is much higher than that of the other resources. Even if the bottleneck is fully saturated, the other resources are still underutilized. Therefore, the queueing delays of the non-bottleneck resources can be approximately ignored. We use machine-repairman model's delay station to represent the sum of the service times of all non-bottleneck resources. As the delay station can abstractly represent multiple distributed resources, real systems of different topologies (e.g., 3 machines or 7 machines) can be represented by this single model, so long as they have a clearly defined bottleneck. Many real systems do satisfy this requirement.

The machine-repairman model can predict event-processing throughput and resource utilization level under different thread configurations [12]. We modified our implementation of TCC to take throughput numbers from the model instead of a live system. This allows us to systematically evaluate TCC under a wide range of hypothetical workloads.

Figure 5(a) shows the number of threads recommended by TCC and the corresponding CPU utilization level. Here we assume that the CPU of the NCI server is the bottleneck resource, and it has 8 CPUs. CPU utilization is affected by the blocking ratio $r$, which is defined as the service time ratio of the delay station to the bottleneck resource. As $r$ increases, each thread blocks longer at the delay station, and hence more threads are needed to drive up CPU utilization. As $r$ varies, TCC is able to adjust the number of threads accordingly to keep high CPU utilization while avoiding complete saturation.

Figure 4(b) shows the event-escalation model, where the NCI server processes an event and then invokes an external program, e.g., an instant messaging server. This model differs from the machine-repairman model in that it does not assume the queueing delays of the non-bottleneck resources are negligible. Figure 5(b) shows the performance of TCC when both machines have 8 CPUs. The $x$-axis is the service time ratio $r$ of the external program to the NCI server. The $y$-axis is the CPU utilization of the bottleneck resource. The bottleneck is the NCI server if $r<1$, or the external program if $r>1$. The lowest utilization 88% occurs when $r=1$, i.e., when the utilization levels of two machines are identical. In this case, more threads are needed to simultaneously drive both machines to high utilization.

Figure 4(c) shows the event-enrichment model, where the NCI server processes an event, enriches it with data fetched from an external database, and writes it back to the event source. This is a widely used topology in real deployments. Figure 5(c) shows the performance of TCC when each of the three machines has have 8 CPUs. The $x$-axis is the service time ratio $r$ of the database to the NCI server. The database and the event source have the same mean service time. The $y$-axis is the utilization of the bottleneck. The lowest utilization 85% occurs when $r = 1$, i.e., when the utilization levels of the three machines are identical.

Results in Figure 5 show that TCC can drive the bottleneck resource to high utilization under different workloads and deployment topologies. On the other hand, TCC may underutilize resources in some cases, e.g., when processing one event goes through a large number of servers whose utilization levels are identical (i.e., $r$=1). To reduce resource waste in this worst case, one might be tempted to make TCC more aggressive in adding threads. However, this would also make TCC less friendly in resource sharing.

### 3.3 Friendly Resource Sharing

Below, we derive the conditions for friendly resource sharing and demonstrate that, with a proper configuration, TCC shares resources in a friendly manner with an uncontrolled competing program. Moreover, multiple instances of TCC also share resources in a friendly manner. We begin our discussion with the basic two-NCI-server scenario.

Suppose two NCI servers independently execute TCC. If each server has its own internal bottleneck that limits its throughput, TCC will independently drive each server to almost full utilization. A more challenging case is that a shared bottleneck resource limits the throughput of both NCI servers, e.g., a shared database. Below, we will show that, when the shared bottleneck is saturated, the two NCI servers take turns to reduce their threads until the bottleneck resource is relieved of saturation.

Suppose the bottleneck resource is fully saturated, two NCI servers $X$ and $Y$ are identical, and they currently run $x_0$ and $y_0$ threads, respectively, where $x_0 \leq y_0$. A TCC tuning cycle consists of the tuning steps starting from the base state and finally settling in the steady state. We use $i$ to number TCC's tuning cycles in increasing order, and assume $X$ and $Y$ take turns to execute in the tuning cycles, i.e., if $X$ executes in cycle $i$, then $Y$ will execute in cycle $i+1$. Let $x_i$ and $y_i$ denote the numbers of $X$ and $Y$'s threads at the end of tuning cycle $i$.

**Theorem 1** *If TCC's parameters $p$, $q$, and $w$ satisfy Equations (1) and (2) below, then $X$ and $Y$ will take turns to reduce their threads (i.e., $y_0 > x_1 > y_2 > x_3 \cdots$) until the bottleneck is relieved of saturation.*

$$q \quad > \quad \frac{p(p+1)}{p+2} \tag{1}$$

$$w \quad \geq \quad 1-(\frac{p}{q}-1)^2 \tag{2}$$

*Moreover, if TCC's parameters satisfy (1) and (2), a TCC instance shares resources with an external competing program in a friendly manner.*

**Proof sketch:** Suppose $X$ is in the process of tuning its configuration, and just finished increasing its threads from $\frac{x}{1+p}$ to $x$. When $X$ uses $x$ threads to compete with $Y$'s $y_0$ threads, $X$'s throughput is $f(x, y_0) = \frac{x}{x+y_0}C$, where $C$ is the maximum throughput of the bottleneck. TCC keeps adding threads so long as every $p$% increase in threads improves throughput by $q$% or more. Therefore, $X$ continues to add more threads if and only if

$$\frac{f(x, y_0)}{f(\frac{x}{1+p}, y_0)} \geq 1+q \ \ , \tag{3}$$

which is equivalent to $x \leq (\frac{p}{q}-1)y_0$. Let $\widehat{y}$ denote the upper bound of this condition:

$$\widehat{y} = (\frac{p}{q}-1)y_0 \ . \tag{4}$$

Suppose $X$ runs no more than $\widehat{y}$ threads in the base state. (This assumption holds if (2) holds.) $X$ keeps adding threads so long as its current number of threads is no more than $\widehat{y}$. Hence, when $X$ stops adding threads, its final number $x_1$ of threads falls into the range

$$\widehat{y} \ < x_1 \leq (1+p)\widehat{y} \ \ . \tag{5}$$

$X$ ends up with fewer threads than $Y$ if $(1+p)\widehat{y} < y_0$. From (4), this condition is equivalent to (1).

When $X$ uses $x_1$ threads to compete with $Y$'s $y_0$ threads, $X$'s share of the bottleneck is bounded by

$$1-\frac{q}{p} \quad < \quad \frac{x_1}{x_1+y_0} \quad \leq \quad \frac{(1+p)(p-q)}{p(1+p-q)}. \tag{6}$$

This bound is derived from (4) and (5).

Now suppose $Y$ executes TCC after $X$ settles with $x_1$ threads. $Y$ first reduces its threads by $w$% in the base state. Following (4), we define

$$\widehat{x} = (\frac{p}{q}-1)x_1 \ . \tag{7}$$

If $Y$'s base state has no more than $\widehat{x}$ threads, i.e., if

$$(1-w)y_0 \leq \widehat{x} \ , \tag{8}$$

then we can follow (5) to obtain the bound of $Y$'s final number $y_2$ of threads when $Y$ stops adding threads:

$$\widehat{x} \ < y_2 \leq (1+p)\widehat{x} \ \ . \tag{9}$$

From (4), (5), and (7), we know that (8) holds if (2) holds.

TCC's default parameters are $p$=25%, $q$=14%, and $w$=39%, which satisfy (1) and (2). Therefore, it follows from (5) and (9) that $y_0 > x_1 > y_2$. This reduction in threads continues as $X$ and $Y$ repeatedly execute TCC, until the bottleneck is relieved of saturation.

Following the approach above, one can also show that TCC shares resources in a friendly manner with an external competing program that generates a constant workload at the shared bottleneck resource. In the face of competition, TCC dynamically adjusts the number of processing threads so that it consumes about 44–49% of the bottleneck resource. This range is obtained by substituting the default parameters ($p$=25% and $q$=14%) into (6). By contrast, if one uses a configuration that does not satisfy (1), TCC's consumption of the bottleneck resource could be unfairly high, e.g., reaching 80–83% for the configuration $p$=25% and $q$=5%.

The analysis above focuses on the base state and the add-thread state. The remove-thread state removes threads to avoid saturation, which makes TCC even more friendly in resource sharing. Therefore, Theorem 1 holds if the remove-thread state is taken into account. ■

With a proper configuration, a TCC instance shares resources in a friendly manner with an external competing program, and two TCC instances also share resources in a friendly manner. Three or more instances of TCC share resources in a friendly manner only if they execute in a loosely synchronized fashion, i.e., they move out of the steady state into the base state roughly at the same time. When the shared bottleneck is saturated and multiple TCC instances attempt to add threads at the same time, they will observe little improvement in throughput and gradually remove threads until the bottleneck is relieved of saturation. A detailed analysis is omitted here. In an NCI cluster, the master can serve as the coordinator to enforce loose synchronization. Using loosely synchronized execution to enforce friendly resource sharing has also been proposed in Tri-S [27], although its application domain is TCP congestion control.

### 3.4 Accurate Performance Measurement

TCC repeatedly adds threads so long as every $p$% increase in threads improves throughput by $q$% or more. Let $C_1$ and $C_2$ denote the configurations before and after adding the $p$% threads, respectively. (This section uses the add-thread state as example. The remove-thread state can be analyzed similarly.) In a noisy environment, throughput is a stochastic process and accurate measurement is challenging. On the one hand, the throughput of a configuration can be measured more accurately if TCC stays in that configuration longer and takes more measurement samples. On the other hand, we want to minimize the measurement time so that TCC responds to workload changes quickly.

We formulate the issue of accurate performance measurement as an optimization problem. The optimization goal is to minimize the total number of samples collected from configurations $C_1$ and $C_2$, and the constraint is to ensure a high probability of making a correct control decision. It turns out that the number of samples needed to make a reliable decision is proportional to the variance of event-processing time (i.e., more samples are needed if the system is volatile), and inversely proportional to the throughput improvement threshold $q$ (i.e., more samples are needed if we want to tell even a small performance difference between two configurations).

Below, we present our statistical approach for performance measurement, our method for handling unstable event arrival rate, and our heuristic for filtering out large noises caused by extreme activities such as Java garbage collection.

#### 3.4.1 Our Experiment Design Approach

We use subscript $i$ to differentiate the two configurations $C_i$, $i = 1, 2$. For configuration $C_i$, let random variable $X_i$ denote the inter-departure time between the completion of event processing. Denote $\mu_i$ and $\sigma_i^2$ the mean and variance of $X_i$. Suppose we take $n_i$ samples of $X_i$, denoted as $X_{ij}$, $1 \le j \le n_i$, and these samples are independent and identically distributed. Denote $\overline{X_i}$ the sample mean of $X_{ij}$. According to the central limit theorem, regardless of the distribution of $X_i$, $\overline{X_i}$ is approximately normally distributed, $\overline{X_i} \sim N(\mu_i, \sigma_i^2/n_i)$.

Let $Y = \overline{X_1} - \overline{X_2}$, which represents the performance difference between $C_1$ and $C_2$. Assuming $\overline{X_1}$ and $\overline{X_2}$ are independent, Y is also approximately normally distributed, $Y \sim N(\mu_y, \sigma_y)$, where

$$\mu_y = \mu_1 - \mu_2 \tag{10}$$
$$\sigma_y^2 = \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}. \tag{11}$$

The mean throughput of configuration $C_i$ is $1/\mu_i$. TCC continues to add threads if the throughput ratio $\frac{1}{\mu_2}/\frac{1}{\mu_1} \ge 1 + q$, where $q$ is the throughput improvement threshold. Considering (10), this is equivalent to $\mu_y \ge \mu'$, where

$$\mu' = \frac{q}{1+q}\mu_1. \tag{12}$$

We want to collect a minimum number of samples, $n = n_1 + n_2$, so that the variance $\sigma_y^2$ in (11) is small enough and we can state with high confidence either Prob$\{Y \ge \mu'\} \ge 1-\alpha$ or Prob$\{Y < \mu'\} \ge 1-\alpha$ holds. Here 1-$\alpha$ is the confidence level ($0<\alpha<0.5$). However, in the worst case when $\mu_y = \mu'$, both Prob$\{Y \ge \mu'\}$ and Prob$\{Y < \mu'\}$ are always 0.5, no matter how many samples we collect. This precludes us from deciding whether $C_2$ is significantly better than $C_1$. We use an indifference zone $[L, H]$ to handle the case when $\mu_y \approx \mu'$.

$$L = (1 - \beta/2)\,\mu' \tag{13}$$
$$H = (1 + \beta/2)\,\mu' \tag{14}$$

Here $\beta$ is a small constant, e.g., $\beta$=0.1. Now we want to collect just enough samples so that at least one of the two conditions below holds:

$$\text{Prob}\{Y \ge L\} \ge 1 - \alpha, \quad \text{or} \tag{15}$$
$$\text{Prob}\{Y \le H\} \ge 1 - \alpha\,. \tag{16}$$

TCC adds more threads if only (15) holds, or if both (15) and (16) hold but Prob$\{Y \ge L\} \ge$ Prob$\{Y \le H\}$.

Let $Z \sim N(0, 1)$, and Prob$\{Z \le Z_{1-\alpha}\} = 1 - \alpha$. Combining (15) and (16), we have

$$\sigma_y \le \frac{1}{Z_{1-\alpha}} \max(H - \mu_y\ ,\ \ \mu_y - L)\,. \tag{17}$$

Combing (11) and (17), the problem of minimizing the total number of measurement samples can be formulated as the optimization problem below.

**Minimize** $\quad n = n_1 + n_2$

**Subject to**

$$\sigma_y^2 = \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2} \le \left\{\frac{\max(H - \mu_y,\ \mu_y - L)}{Z_{1-\alpha}}\right\}^2 \tag{18}$$
$$n_1, n_2 > 0 \tag{19}$$

Solving this problem using Lagrange multipliers, we obtain the minimum number of samples we need:

$$\widehat{n}_1 = \sigma_1(\sigma_1+\sigma_2)\left\{\frac{Z_{1-\alpha}}{\max(H-\mu_y,\ \mu_y-L)}\right\}^2 \quad (20)$$

$$\widehat{n}_2 = \sigma_2(\sigma_1+\sigma_2)\left\{\frac{Z_{1-\alpha}}{\max(H-\mu_y,\ \mu_y-L)}\right\}^2 \quad (21)$$

Both $\widehat{n}_1$ and $\widehat{n}_2$ have the largest value when

$$\mu_y = \frac{H+L}{2} = \mu'. \quad (22)$$

When collecting samples for $C_1$, we have no data for $C_2$ and hence $\mu_y$ is unknown. We have to make the conservative assumption in (22). As $C_1$ and $C_2$ are close, we assume $\sigma_1 \approx \sigma_2$. With these assumptions, (20) is simplified as (23) below. (Note that it is possible to run $C_1$ and $C_2$ back and forth in an interleaving fashion in order to accurately estimate $\mu_y$ rather than conservatively using (22) for $\mu_y$, but this would complicate TCC's state machine in Figure 3.)

$$\widehat{n}_1 = 8\left(\frac{\sigma_1 Z_{1-\alpha}}{H-L}\right)^2. \quad (23)$$

Finally, combining (12), (13), (14), and (23), we have

$$\widehat{n}_1 = 2\, Z_{1-\alpha}^2 \left(\frac{1}{\beta}\right)^2\left(1+\frac{1}{q}\right)^2\left(\frac{\sigma_1}{\mu_1}\right)^2. \quad (24)$$

The minimum number of samples for $C_2$ can be derived from (18) and (23):

$$\widehat{n}_2 = \frac{(\sigma_2 Z_{1-\alpha})^2}{\{\max(H-\mu_y\ ,\ \ \mu_y-L)\}^2 - \frac{(H-L)^2}{8}}. \quad (25)$$

When collecting samples for $C_2$, we have data for both $C_1$ and $C_2$, and hence can estimate $\mu_y$ from (10).

### 3.4.2 Practical Issues

Our method does not rely on any assumption about the exact distribution of $X_i$, but needs to estimate the mean $\mu_i$ and variance $\sigma_i^2$, as they are used in (24) and (25). TCC estimates them by taking $n_i^*$ initial samples from configuration $C_i$, and then uses the sample mean $\mu_i^*$ and sample variance $S_i^2$ to replace $\mu_i$ and $\sigma_i^2$. In practice, we observe that sometimes the event-processing engine experiences long pauses caused by extreme activities such as Java garbage collection or startup of a heavy external program. For example, on a fragmented large heap, Java garbage collection can take as long as 20 seconds.

These long pauses are not an inherent part of the variance in service time, but they make the calculated sample variance $S_i^2$ (and accordingly $\widehat{n}_i$) unusually large. We address this issue by filtering out abnormally large samples. Empirically, we find that abnormal samples caused by long pauses are rare, and discarding the top 1% largest samples is sufficient to filter them out.

Another challenge is to handle the periodical, bulk-arrival pattern of IT events. After processing one block

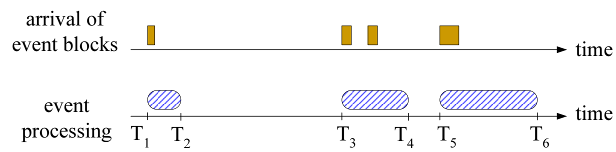



Figure 6: TCC excludes idle time from throughput calculation. Suppose $n$ events are processed in this example. The throughput is calculated as $\frac{n}{(T_2-T_1)+(T_4-T_3)+(T_6-T_5)}$ instead of $\frac{n}{T_6-T_1}$. This method discounts the influence of an unstable event arrival rate and helps TCC operate robustly.

of events, an NCI server remains idle until the next block arrives. TCC excludes this idle time from throughput calculation (see Figure 6), because the low throughput in this case is caused by the lack of input events rather than by a sub-optimal thread configuration.

## 3.5 Selection of Parameter Values

Recall that TCC reduces threads in the base state by $w$%, and then repeatedly add threads so long as every $p$% increase in threads improves throughput by $q$% or more. Now we put together the results in Sections 3.2, 3.3, and 3.4 to guide the selection of these parameters.

Equations (1) and (2) are the conditions for friendly resource sharing. Suppose $p$'s value is already determined. Using queueing models such as those in Figure 4, it can be shown that, relative to $p$, $q$ should be as small as possible in order to achieve maximum throughput. Therefore, for a given $p$, we choose for $q$ the smallest value allowed by (1). Once $p$ and $q$ are determined, we choose for $w$ the smallest value allowed by (2), because a small $w$ keeps more threads in the base state and allows TCC to finish an exploration cycle more quickly. Table 1 lists the appropriate values of $q$ and $w$ for different $p$.

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $p$ | 10% | 15% | 20% | **25%** | 30% | 35% | 40% | 45% | 50% |
| $q$ | 5.4% | 8.2% | 11.5% | **14%** | 17% | 20.5% | 24% | 27% | 31% |
| $w$ | 28% | 32% | 33% | **39%** | 42% | 50% | 56% | 56% | 63% |

Table 1: Appropriate values of $q$ and $w$ for a given $p$.

The next step is to choose a configuration in Table 1. This table as well as (1) and (2) shows that both $q$ and $w$ increase as $p$ increases. Equation (24) suggests that a large $q$ is preferred, because it allows TCC to make a control decision with fewer measurement samples. On the other hand, we prefer a small $w$, as it keeps more threads in the base state. Moreover, we prefer a moderate $p$, because a large $p$ has a higher risk of moving the system into severe thrashing in a single tuning step, whereas a small $p$ may require many tuning steps to settle in a new steady state after a workload change. To strike a balance between all these requirements, we choose ($p$=25%, $q$=14%, $w$=39%) as our default configuration.

In the remove-thread state, TCC repeatedly removes $r$% threads until the throughput becomes a certain fraction (e.g., 95%) of the maximum throughput achieved during a tuning cycle. The remove-thread state does fine tuning and we use $r$=10% by default.

# 4 Experimental Results

We have implemented TCC in Java and integrated it with IBM Tivoli Netcool/Impact [16]. We have evaluated TCC under a wide range of workloads. Experiments demonstrate that an NCI cluster is scalable, and TCC can handle various types of bottleneck resources. We also compare TCC with revised versions of TCP Vegas [4].

Unless otherwise noted, each machine used in the experiments has 5GB memory and two 2.33GHz Intel Xeon CPUs, running Linux 2.6.9. All the machines are hosted in an IBM BladeCenter, where the network round-trip time is only 90$\mu$s. The network delay of a large enterprise's IT environment can be much longer, e.g., varying from 1ms to 100ms when the database with customer profiles is managed at a central remote site for security reasons. To evaluate the effect of network delay, in some experiments, the messages between two machines go through a software router that allows us to introduce message delays in a controlled manner.

## 4.1 NCI Cluster Scalability

Figure 7 shows the scalability of an NCI cluster running TCC, when executing an event-enrichment policy that is widely used in real deployments. The topology of this experiment is shown in Figure 4(c). The event source is Netcool/OMNIbus ObjectServer 7.1 [15]. We developed a tool to automatically feed IT events to ObjectServer, from which the master NCI server fetches events. The external database is MySQL 4.1.12. When processing one event, an NCI server does some local analysis, fetches service contextual information from MySQL, adds it into the event, and finally writes the enriched event back to ObjectServer. In this setup, MySQL caches all data in memory and NCI servers are the bottleneck.

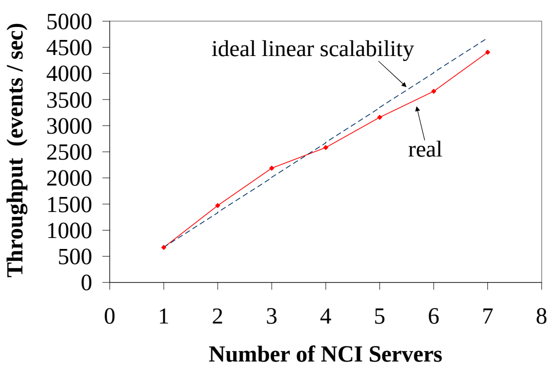



Figure 7: Scalability of NCI.

In Figure 7, the NCI cluster shows almost linear scalability, because the NCI servers fetch events in batches, and the slave NCI servers directly retrieve data from MySQL and write events back to ObjectServer without going the master. In addition, the linear scalability is also due to another algorithm we designed to dynamically regulate the event-fetching rate and event batch size so that the event-processing pipeline moves smoothly without stall. This feature is beyond the scope of this paper.

## 4.2 CPU Bottleneck

In the rest of the experiments, we study the detailed behavior of TCC. These experiments use the event-escalation topology in Figure 4(b), in which the NCI server processes an event and then invokes an external program through its HTTP/XML interface for further processing. Below, we simply refer to this external program as the "Web application" and its hosting machine as the "Web machine." The IPL script executed by the NCI server is specially designed so that we can control its service time on the NCI server. Similarly, the service time of the Web application can also be controlled. Both service times follow a Pareto distribution $p(x) = k\frac{C^k}{x^{k+1}}$, where $k = 2.5$. We adjust $C$ to control the service time.

Figure 8(a) shows the CPU utilization ("NCI-CPU" and "Web-CPU") and the number of threads in an ex-

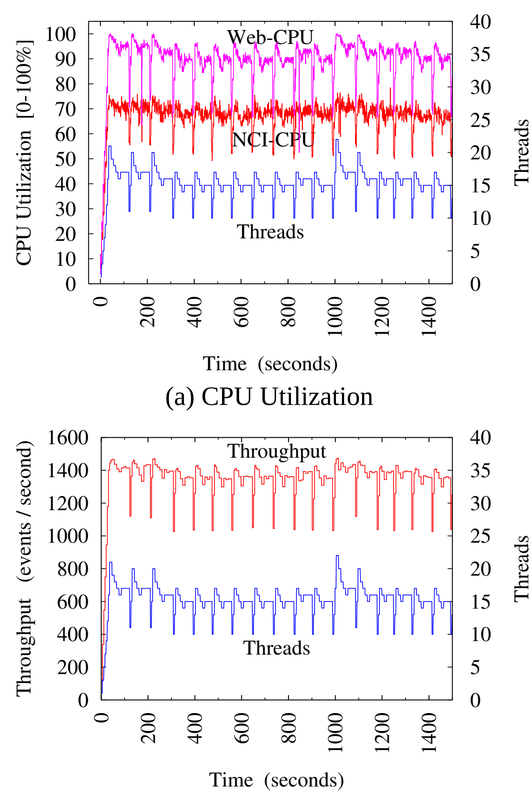



Figure 8: The Web machine's CPU is the bottleneck.

periment where one NCI server works with the Web application. The $x$-axis is the wall clock time since the experiment starts. In real deployments, after processing one block of events, the NCI server remains idle until the next block arrives. This experiment generates IT events in such a way that the NCI server never becomes idle. Otherwise, the CPU utilization would drop to 0 during repeated idle time, making the figure completely cluttered. We conducted separate experiments to verify that the idle time between event blocks does not change TCC's behavior, because TCC excludes the idle time from throughput calculation (see Figure 6).

In this experiment, the mean service time is 1ms for NCI and 1.3ms for the Web application. (Note that the actual service times are random variables rather than constants.) Therefore, the Web machine is the bottleneck. The messages between the NCI server and the Web application go through the software router, which adds about 5ms delay in round trip time. The curves show periodical patterns. Each period is a complete tuning cycle during which TCC starts from the base state and eventually moves back to the steady state. In real deployments, TCC operates in the steady state for a relatively long period of time before it starts the next round of exploration. In this experiment, TCC is configured to stay in the steady state for only about 50 seconds. Otherwise, the curves would be mostly flat.

During the first tuning cycle in Figure 8(a), TCC exponentially increases the number of threads. At time 85 seconds, it moves into the steady state for the first time with 17 threads. During latter tuning cycles, the steady-state threads vary between 15 and 17. This oscillation is due to noisy measurement data. Regardless, TCC avoids saturating the bottleneck resource, and the Web machine's CPU utilization stays around 90%.

Figure 8(b) shows event-processing throughput, which closely follows CPU utilization in Figure 8(a). This is because throughput is proportional to the utilization of the bottleneck resource (i.e., CPU in this experiment). Due to space limitation, below we omit throughput figures and focus on bottleneck resource utilization.

### 4.3 Memory Bottleneck

The experiment in Figure 9 evaluates how TCC works with memory bottleneck and how it recovers from memory thrashing. This experiment uses machines with relatively more CPUs and less memory in order to trigger memory thrashing—each machine has eight 3.2GHz Intel Xeon CPUs and 1GB memory. The mean service time is 8ms for NCI and 1ms for the Web application. The message delay is set to 50ms. Initially, the NCI server's CPU is the bottleneck, and TCC uses 69 threads in the steady state to drive its utilization to 95%.

At time 496 seconds, the NCI server starts to invoke another API of the Web application, which consumes

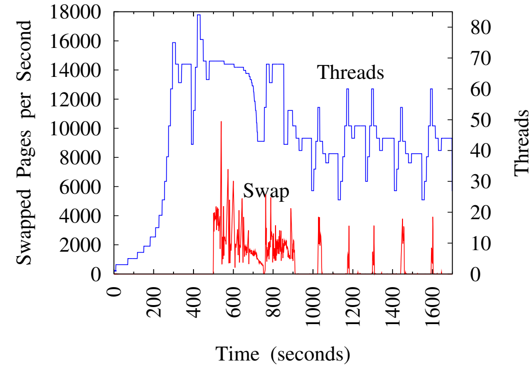



Figure 9: Memory bottleneck and memory thrashing.

a large amount of memory on the Web machine. In total, 69 concurrent threads consume more than 1GB physical memory and immediately drive the Web machine into memory thrashing. Figure 9 reports the Web machine's page swaps monitored through */proc/vmstat*. At time 496 seconds, the free memory drops sharply from 934MB to 19MB, page swaps increase from 0 to 4,000 pages/second, and the event-processing throughput drops from 1,011 events/second to 58 events/second. TCC detects this radical throughput change and restarts thread exploration. By time 945 seconds, TCC reduces steady-state threads down to 44. The Web machine becomes completely free of page swapping, its free memory rises to 106MB, and the throughput increases to 625 events/second. The tuning cycles are relatively long because the throughput is extremely low during memory thrashing and TCC needs time to collect samples.

After time 1,000 seconds, when TCC periodically re-explores new thread configurations, it increases the number of threads beyond 50, and causes page swapping to happen again (see the repeated spikes on the "Swap" curve after time 1,000 seconds). TCC observes that adding threads actually decreases throughput. It then removes threads and avoids thrashing. This experiment demonstrates that TCC can not only recover from memory thrashing but also avoids moving into thrashing.

### 4.4 Disk Bottleneck

The experiment in Figure 10 evaluates how TCC works with a disk bottleneck. Each machine used in this experiment has eight CPUs. The mean service time is 1ms for NCI and 2ms for the Web application. The message delay is set to 20ms. Initially, the Web machine's CPU is the bottleneck, and TCC uses 107 threads in the steady state to drive its utilization to 95%.

At time 247 seconds, the NCI server starts to invoke another API of the Web application, which performs random search in a 60GB on-disk database. Now the bottleneck shifts to the Web machine's disk. The Web machine's CPU utilization drops from 95% to 5%, while

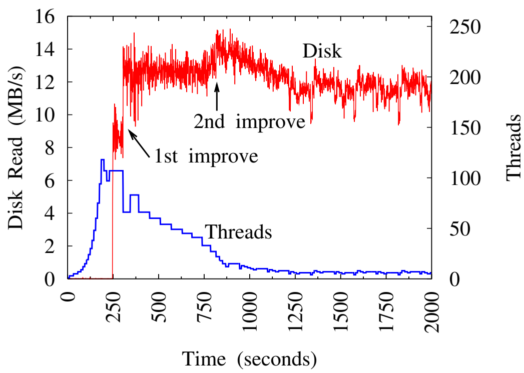



Figure 10: The Web machine's disk is the bottleneck. Removing threads actually improves disk throughput.

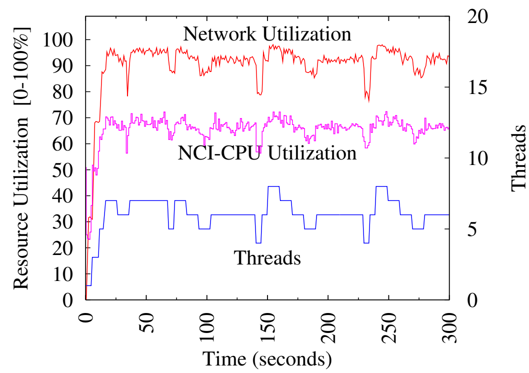



Figure 11: Network bandwidth is the bottleneck.

the amount of data read from disk (monitored through */proc/diskstats*) increases from 0 to 9MB/s. At time 305 seconds, TCC enters the base state and reduces threads from 107 to 66. With fewer threads, the disk throughput actually increases from 9MB/s to 12.5MB/s (*"1st improve"* in the figure). Note that the disk throughput is proportional to the event-processing throughput. When TCC reduces the number of threads down to 22 at time 816 seconds, the disk throughput further increases to 14MB/s (*"2nd improve"* in the figure). TCC continues to remove threads to avoid saturation. Eventually it stabilizes around 7 threads in the steady state, and the Web machine's CPU utilization is only 1.5%. This experiment demonstrates that TCC can radically remove unnecessary threads (from 107 down to 7) when disk is the bottleneck, and disk can actually achieve higher throughput with fewer threads.

### 4.5 Network Bottleneck

For the experiment in Figure 11, the NCI server exchanges a large amount of data with the Web application when processing events. The mean service time is 1.5ms for NCI and 1ms for the Web application. There is no extra message delay between machines. The NCI server has higher CPU utilization than the Web machine, but the bottleneck of the whole system is network. Even if CPUs are still underutilized, TCC stops adding threads when the network bandwidth utilization reaches around 92%. Note that TCC works by observing changes in event-processing throughput, without even knowing which resource is actually the bottleneck.

### 4.6 NCI Working with a Competing Program

The experiment in Figure 12 evaluates TCC's response to an external program that competes for the bottleneck resource. The mean service time is 1ms for NCI and 1.3ms for the Web application. The Web machine is the bottleneck. The message delay is set to 5ms. At time 286 seconds, an external program is started on the Web machine to compete for CPU. During the tuning cycle between time 293 and 368 seconds, TCC reduces steady-state threads from 17 to 10, and the Web machine is relieved of 100% saturation starting from time 341 seconds. The tuning cycle between time 406 and 441 seconds further reduces steady-state threads from 10 to 8. The external program terminates at time 477 seconds, and the Web machine's CPU utilization drops sharply from 95% to 49%. During the following tuning cycle between time 483 and 553 seconds, TCC quickly increases steady-state threads from 8 to 17, and drives the Web machine's CPU utilization back to 95%. This experiment demonstrates that TCC shares resources with a competing program in a friendly manner, and responds quickly when the bottleneck's available capacity increases.

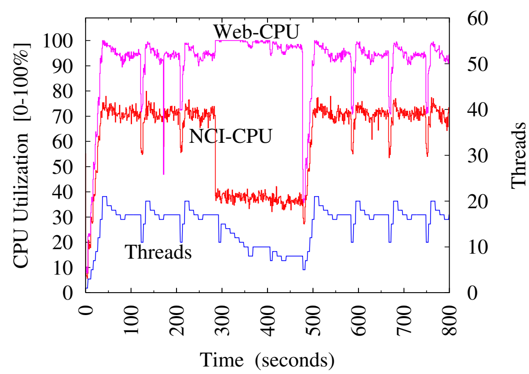
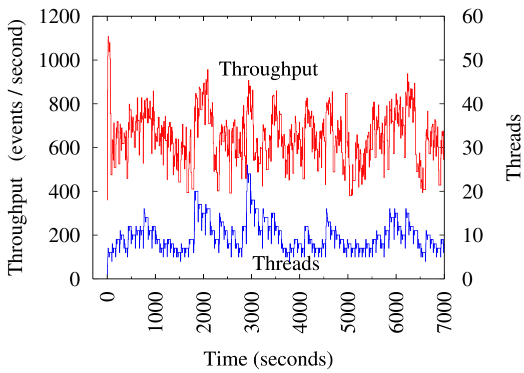


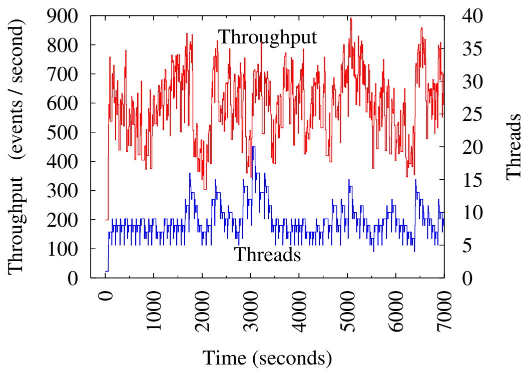

Figure 12: An external program competes for the bottleneck resource, which is the Web machine's CPU.

### 4.7 Two NCI Servers Sharing a Bottleneck

The experiment in Figure 13 runs two NCI servers to share the Web application. The mean service time is 1ms for NCI and 1.5ms for the Web application. The Web application is the shared bottleneck that limits the throughput of both NCI servers. This experiment introduces no extra message delays between machines. Server $X$ starts first and quickly drives the throughput to as high as 1,100



(a) Server X



(b) Server Y

Figure 13: Two competing NCI servers work with the Web application. The latter is the shared bottleneck.

events/second (see the throughput spike around time 0). After server $Y$ starts, $X$ and $Y$ share the bottleneck resource in a friendly manner. Their throughput oscillates around 550 events/second and their steady state oscillates around 8 threads. Sometimes one server mistakenly increases its threads beyond its fair share (due to noisy measurement data), which causes the other server to also increase its threads in order to get its fair share (see the thread spikes around time 3,000 seconds). However, the friendly resource sharing logic built in TCC ensures that the competition does not escalate, and they gradually reduce their threads back to the normal level.

### 4.8 Comparison of Different Controllers

To our knowledge, no existing controllers are designed to maximize the throughput of general distributed systems while not saturating the bottleneck resource. The closest to TCC is TCP Vegas' congestion avoidance algorithm [4]. It computes the difference $D$ between the actual throughput and the expected throughput, and increases the concurrency level if $D$ is small, or decreases the concurrency level if $D$ is large. The expected throughput is calculated as the product of the concurrency level and a baseline throughput. The baseline throughput is defined as the throughput achieved when the concurrency level is one and the network is completely free of cross traffic. A key challenge is to estimate the baseline throughput when cross traffic exists.

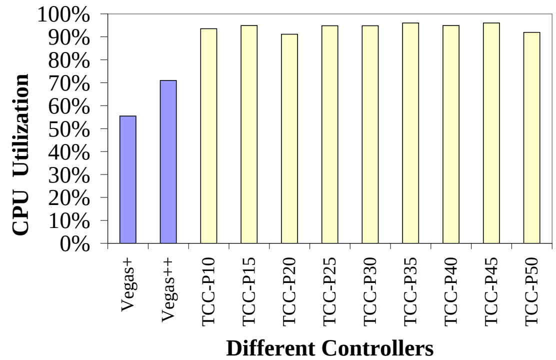


Figure 14: Comparison of different controllers.

TCP Vegas is designed for and works well in the network domain, but it critically relies on an assumption that does not hold in general distributed systems—it assumes a processing unit's service time is constant. Because of this assumption, TCP Vegas can use $\frac{1}{minRTT}$ to approximate the baseline throughput, where $minRTT$ is the minimum round trip time of packets. By contrast, the service time of a server in a general distributed system is inherently a stochastic process. For instance, the service time of a database query may vary over time, depending on the size of the database and the cache status. As a result, the actual baseline throughput for a general distributed system can be much lower than $\frac{1}{minRTT}$.

A complete redesign of TCP Vegas to work for general distributed systems would require (1) a method to estimate the baseline throughput when servers' service times are stochastic processes and there exists cross traffic; (2) proving that the new algorithm shares resources with uncontrolled competing programs in a friendly manner; and (3) demonstrating that the new algorithm can achieve high resource utilization under typical topologies of distributed systems. The first task is especially challenging, and our initial study suggests that a satisfactory solution might not exist at all. We leave it as future work.

In Figure 14, "Vegas+" is our revised version of TCP Vegas. It runs in NCI at the application layer, and controls the number of event processing threads. It adjusts the concurrency level after measuring a stable throughput. In Vegas+, $minRTT$ is the minimum response time of event processing. In this experiment, the mean service time is 1ms for NCI and 2ms for the Web application. The network delay is set to 25ms. The Web machine is the bottleneck, and Vegas+ can only drives its CPU utilization to 55%. Vegas++ in Figure 14 is an enhanced version of Vegas+. It uses an accurate baseline throughput measured offline in a controlled environment that is free of cross traffic. Vegas++ is not a practical online algorithm, but we use it to study the potential of TCP

Vegas. Vegas++ improves the utilization of the bottleneck from 55% to 70%, which is still far from ideal. Vegas+ and Vegas++ use the parameters of TCP Vegas as recommended in [21]. The resource utilization may be improved by tuning these parameters, but the challenge is to prove that, with the new parameters, the algorithm is still friendly in resource sharing.

Vegas+ and Vegas++ are not full redesigns of TCP Vegas, as they do not solve the three challenging redesign tasks described above. Our initial study suggests that those tasks might not have a satisfactory solution at all. Here we use Vegas+ and Vegas++ to emphasize that the problem TCC solves is challenging, and no prior solutions can be easily adapted to solve the problem.

The other bars in Figure 14 show the performance of TCC under different configurations in Table 1 of Section 3.5. For instance, TCC-P25 is TCC's default configuration ($p$=25%, $q$=14%, $w$=39%), and TCC-P10 is ($p$=10%, $q$=5.4%, $w$=28%). With the different configurations, TCC consistently drives the bottleneck resource utilization to 90-95%, showing that our guidelines in Section 3.5 for choosing TCC parameters are effective. Moreover, our guidelines ensure that TCC with these configurations is friendly in resource sharing.

## 5 Related Work

Performance control has been studied extensively for many applications, including Web server [28], search engine [2], storage [18], and scientific applications [25]. To our knowledge, no existing work uses a black-box approach to maximize the throughput of general distributed systems while trying to avoid saturating the bottleneck resource. TCP Vegas [4] is the closest to our algorithm, and a detailed discussion is provided in Section 4.8. Most existing algorithms [2, 23, 28] use a manually-configured and system-dependent response time threshold to guide performance control. If the threshold is set too high, the system will be fully saturated; if the threshold is set too low, the system will be underutilized.

We broadly classify existing controllers into four categories. Each category has an enormous body of related work, and we only review some representative ones.

The first category considers performance optimization as a search problem in a multi-dimensional parameter space. For instance, Active Harmony [25] uses the simplex method to perform the search. Existing methods of this category aggressively maximize performance without considering resource contention with an uncontrolled external program. Moreover, running multiple instances of the controller may result in severe resource saturation as each controller instance attempts to consume 100% of the shared bottleneck resource.

The second category uses classical control theory [13] to regulate performance. It requires the administrator to manually set a performance reference point. The system then adjusts itself to stabilize around this reference point. If we apply this method to Netcool/Impact, the reference point would be achieving 90% bottleneck resource utilization. However, a straightforward implementation would require Netcool/Impact to monitor the resource consumptions of all third-party external programs working with Netcool/Impact, which is impractical in real deployments because of the diversity and proprietary nature of the third-party programs. Moreover, existing methods of this category are not sufficiently "black-box" and require information not available in Netcool/Impact deployment environments. For example, Triage [18] assumes knowledge of every resource-competing application's service-level objectives, and the method in [24] assumes knowledge of every component's performance characteristics obtained from offline profiling.

The third category uses queueing theory [12] to model a system with a fixed topology, and takes actions according to predictions given by the model. For instance, Pacifici et al. [23] use online profiling to train a machine-repairman model, which is used to guide flow control and service differentiation.

The fourth category includes various heuristic methods. SEDA [28] adjusts admission rate based on the difference between the 90-percentile response time and a manually-set target. Like TCP Vegas, Tri-S [27] is also designed for TCP congestion control and requires estimating a baseline throughput. MS Manners [9] regulates low-importance processes and allows them to run only if the system resources would be idle otherwise. It also needs to establish a baseline progress rate.

## 6 Conclusions

We presented TCC, a performance controller for high-volume non-interactive systems, where processing tasks are generated automatically in high volume by software tools rather than by interactive users, e.g., streaming event processing and index update in search engines. TCC takes a black-box approach to maximize throughput while trying to avoid saturating the bottleneck resource. We used analysis to guide the selection of its parameters, and designed a statistical method to minimize measurement samples needed for making control decisions. We implemented TCC and integrated it with IBM Tivoli Netcool/Impact [16]. Experiments demonstrate that TCC performs robustly under a wide range of workloads. TCC is flexible as it makes few assumptions about the operating environment. It may be applied to a large class of throughput-centric applications.

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