Systematically Translating Service Level Objectives into Design and Operational Policies for Multi-Tier Applications

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We propose a systematic and practical approach that combines fine-grained performance modeling with regression analysis to translate Service Level Objectives (SLOs) into design and operational policies for multi-tier applications. These policies can then be used for designing a service to meet the SLOs and monitoring the service thereafter for violations at runtime. We demonstrate that our approach is practical and can be applied to commonly used multi-tier applications with different topologies and performance characteristics. Our approach handles both request-based and session-based workloads and deals with workload changes in terms of both request volume and transaction mix. Our approach is non-intrusive in the sense that it requires no specialized profiling, i.e., the data used in our approach is readily available from normal system and application monitoring. We validate our approach using both the RUBiS e-commerce benchmark and a trace-driven simulation of a business-critical enterprise application. These results show the effectiveness of our approach.

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ABSTRACT

A Service Level Agreement (SLA) contains one or more Service Level Objectives (SLOs) that describe the agreed upon quality requirements at the service-level. In order to manage the service to meet the agreed upon SLA, it is important not only to design a service of the required capacity but also to monitor the service thereafter for violations at runtime. This objective can be achieved by undertaking *SLA Decomposition*, i.e., translating SLOs specified in the SLA into lower-level policies that can then be used for design and enforcement purposes. Such design and operational policies are often constraints on thresholds of lower level metrics. Traditionally, domain experts and administrators bring their knowledge to bear upon the problem of SLA decomposition. This practice is ad-hoc, manual, and static (i.e., done once). This is both costly, and not well suited to dynamic workloads. In the past, there has been a number of efforts to develop more automated and dynamic solutions, but these approaches have many limitations and hence pose major challenges to their applicability in practice.

In this paper, we propose a systematic and practical approach that combines fine-grained performance modeling with regression analysis to translate service level objectives directly into design and operational policies for multi-tier applications. We demonstrate that our approach is practical and can be applied to commonly used multi-tier applications with different topologies and performance characteristics. Our approach handles both request-based and session-based workloads and deals with workload changes in terms of both request volume and transaction mix. Our approach is non-intrusive in the sense that it requires no specialized profiling, i.e., the data used in our approach is readily available from normal system and application monitoring. We validate our approach using both the RUBis e-commerce benchmark and a trace-driven simulation of a business-critical enterprise application. These results show the effectiveness of our approach.

1. INTRODUCTION

A Service Level Agreement (SLA) captures the agreed upon guarantees between a service provider and its customer. The ability to deliver according to a pre-defined SLA is an increasingly critical need in today's highly complex and dynamic IT environments.

One of the key tasks to SLA management is *SLA decomposition*, translating the high level service objectives to low level design and operational policies that can be then used to ensure the Service Level Objectives (SLOs) are met. Given an application/service and its corresponding SLOs, the IT operations team undertakes SLA decomposition by determining the design parameters that include identifying the operational level objectives that are relevant and the healthy ranges for various operational metrics to satisfy the SLAs. For example, for a given set of SLOs for an e-commerce application (e.g., response time requirements), domain experts make decisions about low level design and operational policies. A design policy setting usually contains system design parameters such as how many web servers, application servers and database servers must be allocated to satisfy the specified SLOs. An operational policy specifies details of low level metrics (e.g., system resource utilization) to monitor, healthy ranges of these metrics and actions to take when healthy ranges are violated. Such an operational policy can be used for monitoring potential violations and enforcement of SLOs at run time. Once the system is put into production, workloads and associated SLOs may change during operation. As a result, design policies need to be adjusted to ensure current system capacity is sufficient to handle the future workload. Operational policy configurations need to be adjusted as well. Traditionally, domain experts and administrators bring their knowledge to bear upon the problem of SLA decomposition. Most of the time, these decisions are made in an ad-hoc manner based on past experience. This process involves substantial manual effort and adds to the cost of service design and operation. Hence effective and efficient SLA decomposition in an automated fashion is a key requirement in SLA management.

In the past, researchers have made many efforts to address SLA decomposition using techniques such as automated provisioning, capacity planning, and monitoring [16, 17, 20, 28, 29]. Previous studies have utilized performance models to guide resource provisioning and capacity planning [16, 20]. Urgaonkar et al. propose a dynamic provisioning technique for multi-tier applications [16, 17]. All these research efforts separate design and operations into two phases and mostly describe the capacity planning and resource provisioning aspects of the design phase. In addition, these research efforts make several simplifying assumptions. As a result, the practicality and effectiveness of these approaches pose major challenges to their applicability. We have identified four main problems associated with existing solutions that are described below.

First, workloads in real applications are dynamic and vary over time. Unfortunately, most existing solutions take into account the change in the volume of demand only, and assume a fixed or stationary transaction mix [16, 17, 28]. Changes in the volume of transactions (e.g., request rate) or the mixture of transaction types can dramatically alter an application's performance and resource. Hence, a practical decomposition approach must handle workload changes in both the volume and transaction mix.

Second, existing solutions model enterprise application workloads as either request-based (*open workload*) or session-based (*closed workload*) [16, 17, 26, 28]. In reality, workloads are typically *semi-open*, which is significantly different than either an open or a closed model [25]. Hence, a single model approach in most existing solutions is not sufficient to handle the diversity in realistic workloads. A practical approach should support multiple models and choose an appropriate model that is based on the properties of the real workload.

Third, building accurate performance models typically requires input parameters such as resource demand. However, most existing solutions cannot provide the needed model parameters directly. Instead, such information must be obtained through application or system instrumentation. In practice, instrumentation of production applications is rarely done, as it is difficult, costly, and may introduce overhead that degrades the application's performance [29]. Hence, a practical approach should be non-intrusive and passively utilize data that is already available on most systems.

Lastly, most existing solutions are not applicable to the diverse range of design and implementation choices. Many of them make simplifying assumptions about the application infrastructure, such as considering only one server per tier [17, 26] or uniformly distributing the requests across the different tiers [26]. To cope with the diversity and complexity in real applications, a model must be sufficiently general to capture the behavior of applications with different configurations, workloads and performance characteristics.

In this paper, we propose a systematic, non-intrusive and practical SLA decomposition approach to address the above issues. Our approach combines a fine-grain performance model and a regression-based profiling approach to derive low-level operational policies from high-level objectives for multi-tier applications. We formalize the decomposition as a constraint optimization problem, and develop a constraint solver to solve it. Our approach provides the following four key contributions. First, our approach formally characterizes both request-based and session-based workloads. This enables us to choose an appropriate model based on the workload characteristics of the application. Second, our approach models workload as a transaction mix, and systematically creates a resource profile for each transaction type. This fine-grained model enables us to deal with dynamic and non-stationary workloads. Third, we use regression analysis to estimate the model parameters. The data used in our approach is readily available from regular system and application monitoring and requires no additional instrumentation. It is hence practical to apply our approach to production environments. Finally, the proposed modeling technique can model multi-tier applications with different topologies (i.e., any number of tiers and any number of servers at each tier), and different workloads (open and/or closed). As a result, our performance model and decomposition approach can be applied to a vast variety of common multi-tier applications.

The remainder of this paper is organized as follows. Section 2 provides an overview of our approach and our workload model. In Section 3, we describe profiling in detail. We present an analytical performance model for multi-tier applications in Section 4 and our decomposition approach in Section 5. The experimental validation of our approach is presented in Section 6. Related work is discussed in Section 7. Section 8 concludes the paper and discusses future work.

2. OVERVIEW OF OUR APPROACH

2.1 Definition of a Multi-tier Application

Multi-tier applications are common in modern enterprises. Such applications are comprised of a large number of components, which interact with one another in complex patterns. Typically, multi-tier applications are structured into multiple logical tiers. Each tier provides certain functionality to its preceding tier and uses the functionality provided by its successor to carry out its part of the overall request processing. At each tier, a load balancer distributes the overall load among all servers of that tier according to certain scheduling algorithms. Consider a multi-tier application consisting of M tiers, T_1, … T_M. In the simplest case, each request is processed exactly once by each tier and forwarded to its succeeding tier for further processing. Once the result is processed by the final tier T_M, the results are sent back by each tier in the reverse order until it reaches T_1, which then sends the results to the client. In more complex processing scenarios, each request at tier T_i can trigger zero or multiple requests to tier T_{i+1}. For example, a static web page request is processed by the Web tier entirely and will not be forwarded to the other tiers. On the other hand, a keyword search at a Web site may trigger multiple queries to the database tier.

Table 1. Workload definition

Type	Workload Parameters
Open	N: number of transaction types (λ_1, λ_2, … λ_N): transaction mix where λ_i (i =1 …N) is the arrival rate of requests of transaction type i during certain time interval
Closed	N: number of transaction types C: number of users Z: think time π (p_1, p_2, … p_i,…p_N) : transaction mix distribution where p_i (i = 1, …N) is the percentage of requests of transaction type i

2.2 Workload Model Definitions

There are typically a number of transaction types in any multi-tier application. For example, an online auction application has transaction types such as login, browse, bid, etc. In most cases, different transaction types have different service demands on resources. For example, bid transactions in an auction site typically require more CPU time than browse transactions. As previously discussed, empirical workloads tend to be *partially-open,* which means a user arrives and stays for a certain amount of time (and issues a number of requests) before they leave. Previous work has shown that partly-open workloads can be approximated using an open workload if the number of requests in a session is small, and a closed workload otherwise [25]. We consider these two types of workloads in our workload model.

2.2.1 *Open Workload*

In an open (request-based) workload, a new request to the application is only triggered by a new user arrival. The requests are independent of each other and the arrival rate is not influenced by the number of requests that have already arrived and are being processed. The number of users who interact with the application at any time may range from zero to infinity. An open workload is characterized by an average arrival rate of requests or more generally by an arrival distribution. A typical open workload is a transaction mix of different transaction types. In real production systems, the transaction mix changes over time [26]. Assume the total number of transaction types is N. We define an open workload during a certain interval (e.g., 5 minutes) as a vector (λ_1, λ_2, … λ_N) where λ_i is the arrival rate of transaction type i during that interval.

2.2.2 *Closed Workload*

In a closed (session-based) workload, a fixed number of users interact with the application and each of these users issues a succession of requests. A new request from a user is only triggered after the completion of a previous request by the same user. A user submits a request, waits for the response of that request, thinks for a certain time and then sends a new request. The average time elapsed between the response from a previous request and the submission of a new request by the same user is called the "think time", denoted by Z. The next request sent by a user is usually determined by a state transition matrix that specifies the probability to go from one transaction type to another. Assume the number of transaction types is N. The state transition matrix has N rows and N columns where p_{ij} represents the transition probability from transaction type i to transaction type j. Let P denote a state transition matrix of a closed workload and $\pi = (p_i, p_2 \ldots p_N)$ denote the stationary transaction distribution in a user session where p_i presents the percentage of requests of transaction type i sent by the user based on P. We have $\pi P = \pi$ and $\sum_{i=1}^{N} p_i = 1$. We can use the workload with a stationary transaction mix π to approximate the behavior of a closed workload with state transition matrix P [27]. A closed workload is characterized by the number of concurrent users C, the stationary distribution of transaction mix π, and the think time Z.

The open and closed workload models are summarized in Table 1. Unlike many open workload models that assume a static transaction mix and hence use an aggregate request rate to characterize the workload, our transaction vector model captures request rate per transaction type and hence can characterize dynamic transaction mixes. Similarly, by explicitly incorporating the transaction mix distribution as part of the workload parameter in a closed workload, we can capture different behaviors with different transaction distribution.

2.3 Our Approach

An SLA is comprised of multiple Service Level Objectives (SLOs). The task of SLA decomposition is to translate SLOs into design parameters and bounds on low-level system resources such that the high-level SLOs are met. Given a high-level performance SLO and a workload for a multi-tier application (in terms of either a transaction mix for an open workload or a transaction distribution for a closed workload), decomposition provides the resource requirements (e.g., number of servers) to handle the workload and meet the specified SLO. It also finds the healthy state of each component involved in providing the services (e.g., resource utilization). The decomposition process can be summarized as

$$(R, W) \rightarrow (\eta_{web}\ \theta_{web\text{-}cpu},\ \eta_{app},\ \theta_{app\text{-}cpu},\ \eta_{db},\ \theta_{db\text{-}cpu})$$

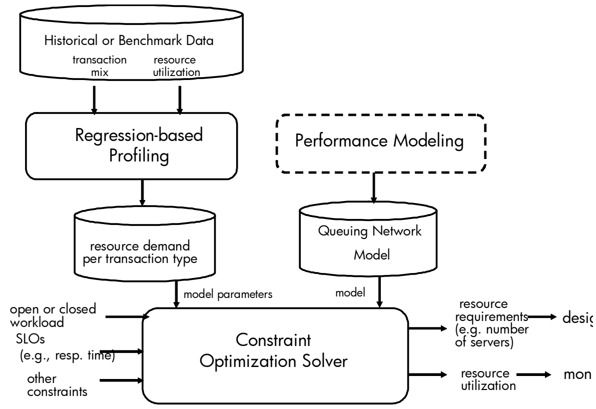


Figure 1. Conceptual architecture

where R and W denote the response time and workload respectively and η is the number of servers at a tier and θ is the resource utilization. SLA decomposition problem is the opposite of a typical performance modeling problem, where the overall system's performance is predicted based on the configuration and resource consumption of the sub-components.

For example, given the performance goal of a 3-tier online e-commerce application (e.g., response time<10 seconds), and any workload in term of transaction mix (e.g., browsing=10 reqs/s, add-to-cart=5 reqs/s, and checkout=4 reqs/s), the decomposition approach determines how many Web servers, application severs and database severs are required to handle the workload while satisfying the specified response time requirement. Decomposition further determines the healthy ranges of the resource utilization of each server (e.g., CPU, I/O, network, etc.) under the configuration during operation.

Our SLA decomposition approach is illustrated in Figure 1. We undertake SLA decomposition in a systematic way. We use analytical performance models to capture the relationship between high-level performance goals (e.g., response time of the overall system), the application topology, and the resource usage of each component (e.g., CPU utilization). In particular, we develop two queueing network models for a multi-tier architecture, where each tier is modeled as a multi-station queueing center. One of the two models is chosen based on the properties of the real workload. We profile the applications and generate the resource demand of each transaction type at each resource. This is obtained by performing a statistical regression analysis on the historical or benchmark data. The profiling results are stored as the application resource profile in a repository. Combining the performance model and the application resource profile, the decomposition problem becomes a constraint satisfaction problem. Given a performance goal (e.g., response time), a workload (open or closed in terms of transaction mix) and any other constraints (e.g., CPU utilization < 50%), the solver takes the application resource profile and the analytical model as inputs and generates a low-level policy setting. The output includes the resource requirements, such as how many servers at each tier are required to meet the SLO and the healthy bounds of resource utilization for each component. The resource requirement is then used for the design and reconfiguration of the application accordingly, while the healthy range is used for monitoring the systems during operation. The developed analytical models and application resource profiles are archived for future reuse. If the workload or response times change, we only need to re-solve the constraint satisfaction problem with new parameters to generate a new policy setting.

3. PROFILING

3.1 Profiling Overview

Profiling creates detailed resource profiles of each component in the application. A resource profile captures the demand of each transaction type at that resource. Per-transaction type resource demand (e.g., a browse transaction's CPU demand at an application server) is independent of the overall transaction mix and hence remains stable despite any changes in a workload. The profile only needs to be created once, and can be used to drive resource demand for different transaction mixes. In order to obtain the resource profile, we first acquire the measurements on the transaction information and the resource consumption in different transaction mixes either from the historical data or through benchmarking. The latter is used for new applications (e.g., in design phase) where no system and application logs are available. We deploy a test environment, apply a variety of transaction mixes to the application and collect the transaction and resource consumption information. Regression analysis is then applied to the data, to derive the per transaction-type resource demands. The resulting resource profile for the application is then stored in a repository. The data required by the regression analysis includes system resource utilization, such as CPU usage, and the application workload information, such as transaction mix. The data is readily available from system and application monitoring logs. This way, our profiling is non-intrusive since it does not require changes to existing applications and systems for instrumentation purposes and hence avoids most of the disadvantages of instrumenting the application. Further, our fine-grained profiles capture the resource demand at per-transaction level and hence can handle dynamic changes in transaction mix. The profiling detail is discussed below.

3.2 Resource Demand Estimation

Two key objectives of profiling are to accurately estimate the resource demands for the application, and to identify the input parameters for the performance model. The accuracy of a performance model depends directly on the quality of its input parameters. Our regression-based profiling is based on the following observations.

(1) Typically, the aggregated resource demand of all transaction types in a workload are measured during the profiling stage. In most cases, the transaction mix is assumed to be static. Hence, the results obtained for a workload only hold for that particular workload with the same transaction mix. This approach cannot be applied to realistic workloads where the percentage of transaction types changes over time.

(2) The resource demands of different transaction types are usually different but the resource demand of a transaction type is relatively fixed irrespective of the transaction mix. Hence, it is better to create a profile for each transaction type (e.g., CPU demand for browse transaction, bid transaction, etc.) instead of creating an aggregated profile for the entire workload. The per-transaction type profile remains stable across different transaction mix.

(3) Few applications are currently instrumented to measure fine-grained transaction resource information. Hence, accurately measuring the service demand of each component requires significant instrumentation of the original application. This is unrealistic in practice. Since the resource demand of each transaction type is relatively static across different transaction mixes, we can derive the parameter of per transaction types using regression-based approaches [26, 27].

(4) The average resource demand of a request in a workload is determined by the distribution of different transaction types in the workload and the service demand of each transaction type. Once we have per-transaction type profiles, given a new transaction mix, the aggregated resource demand can be derived from per-transaction resource demand.

During a certain interval, a resource's usage is the sum of all transaction types' demand at that resource, plus a base utilization to account for background activities that are present in real systems (even when the application is completely idle). Hence, a resource's utilization can be obtained as follows.

$$U = D_0 + \sum_{i=1}^{N} D_i \bullet \lambda_i \quad (1)$$

where U is the resource utilization, N denotes the number of transaction types, D_0 represents the background utilization of the resource, D_i represents the resource demand of a request of transaction type i at that resource, and λ_i is average request rate of transaction type i.

In order to obtain the demand D_i (i=1,… N) at each resource (e.g., CPU, I/O, network), we collect utilization data from each resource U as well as the arrival rates of different transaction types λ_i (i=1, …N) over multiple time intervals (e.g., 5 minutes, 1 hour). These inputs are generally available via system and application monitoring logs.

The goal of profiling is to compute the resource demand of each transaction type at that resource D_1, … D_N. This problem can be solved by using linear regression on a set of equations (1) at multiple intervals. There are numerous different linear regression techniques that could be utilized. In this work, we used Least Squares Regression (LSR) to obtain the resource demands D_i (i =1,…N). Other approaches, such as Least Absolute Deviations Regression (LADR) could also be applied, as they may provide some advantages over LSR (e.g., increased accuracy and robustness).

We repeat the above steps for each resource and generate the application resource profile. The profile consists of a set of resource demands of each transaction type.

4. PERFORMANCE MODEL

Our performance model captures the relationship between the overall application performance as a function of transaction workload, the application configuration, and the resource performance characteristics. We utilize a queuing network model of multi-tier applications. M/M/1 queuing network model is used to evaluate the performance for open workloads, while closed queueing network model is used for closed workloads. Our model is sufficiently general to model any commonly used multi-tier e-commerce application with different application topologies and workloads. Our model also handles multi-class users. The performance model is discussed in detail next.

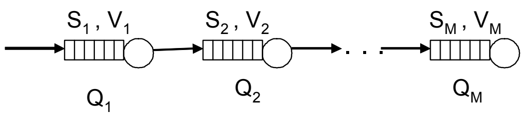


Figure 2. Basic queueing network model

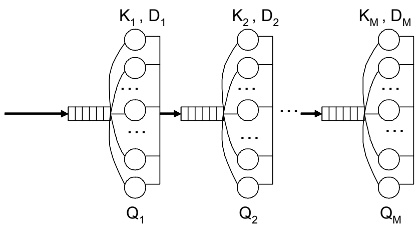


Figure 3. Multi-queue model

4.1 Basic Model

An application with M tiers is modeled as a queueing network of M queues Q_1, Q_2, ...Q_M. (see Figure 2). Each queue represents an individual tier of the application and the underlying server it runs on. A request, after being processed at queue Q_i either proceeds to Q_{i+1} or returns to Q_{i-1}. A transition to the client denotes a request completion (i.e., response to the client). We use V_i to denote the average number of visits to queue Q_i by a request. Our model can handle multiple visits to a tier. Given the user request arrival rate λ, the request arrival rate at tier i can be approximated as $V_i \times \lambda_i$. Given the service demand D_i of a request per visit to tier i, the average service demand per user request at tier i can be approximated as $V_i \times D_i$.

Realistic multi-tier applications typically utilize a multi-server/processor architecture to hand a large number of requests. The application server tier for example may involve one or more application servers (e.g., JBoss). A similar notion is applicable to the database tier which may consist of one or more database servers (e.g., MySQL). In order to capture the multi-server/processor architecture, we enhanced the basic model by using a multi-queue center to model each tier (see Figure 3). In this model, each server/processor in the tier is represented by a queue. The multi-queue model thus is a general representation of a tier. We use K_i to denote the number of servers at tier i. This model represents the multi-server architecture commonly utilized by multi-tier applications.

4.2 Performance Model for Open Workloads

Consider the following notation.

- M: number of tiers (e.g., Web, APP, DB)
- N: number of transaction types (e.g., Browse, Bid)
- R: number of resources types (e.g., CPU, DISK)
- η_k: number of servers at tier k (k = 1, … M)
- ($\lambda_1, \lambda_1 \ldots \lambda_N$): open workload where λ_i is the average request rate of transactions type i
- D_{ik}: service demand of transaction type i at a server of tier k (i =1, … N, k =1,…M)
- U_{kj}: utilization of resource type j at tier k (j=1…R, k = 1, …M)
- i: index of transaction type
- j: index of resource type
- k: index of tier

Assume we have a perfect load balancer that evenly distributes the load among all servers of each tier. We model a tier with K servers as K M/M/1 queues. The total service time of a request at tier k is the weighted sum of each transaction type's service time $\sum_{i=1}^{N} \frac{\lambda_i}{\eta_k} \bullet D_{ik}$. The waiting time on a resource type k at tier j is $\sum_{j=1}^{R} \frac{U_{jk}^2}{1-U_{jk}}$. The total residence time of all requests at tier k is the service time plus the waiting time $\sum_{i=1}^{N} \frac{\lambda_i}{\eta_k} \bullet D_{ik} + \sum_{j=1}^{R} \frac{U_{jk}^2}{1-U_{jk}}$. The average response time is the sum of the residence times at each tier divided by the overall request rate.

$$RT = \sum_{k=1}^{m} \frac{\sum_{i=1}^{N} \frac{\lambda_i}{\eta_k} \bullet D_{ik} + \sum_{j=1}^{R} \frac{U_{jk}^2}{1-U_{jk}}}{\sum_{i=1}^{N} \frac{\lambda_i}{\eta_k}} \qquad (2)$$

Given the application profile, the utilization U of each resource can be obtained as follows

$$U = D_0 + \sum_{i=1}^{N} D_i \bullet \lambda_i / \eta \qquad (3)$$

The overall resource demand D of a transaction type at a server is the sum of all resource demand (e.g., CPU, DISK) at that server. This model is sufficiently general to capture typical multi-tier applications with multiple transactions types and multiple servers at each tier.

Given the parameters of the applications, the application resource profile and an open workload

- M: number of tiers (e.g., Web, APP., DB)
- N: number of transaction types (e.g., Browse, Bid)
- R: number of resources types (e.g., CPU, DISK)
- η_k: number of servers at tier k (k = 1, … M)
- D_{ik}: service demand of transaction type i at a server of tier k
- ($\lambda_1, \lambda_1 \ldots \lambda_N$): transaction mix

Equation (2) is used to predict the response time and Equation (3) is used to derive the resource utilization. Unlike most performance models, our model takes into account the multi-server structure and represents multi-tier applications at a fine-granular level (i.e., per transaction type per resource characterization). As a result, our performance model can be applied to general multi-tier applications with different application topology and open workload with dynamic transaction mix.

4.3 Performance Model for Closed Workloads

Consider a closed workload with C users and think time Z. In order to capture the closed workload and the concurrency of multiple users, we use a closed queueing network, where we model C concurrent users as C delay resources with each of them exhibiting a service demand Z. Figure 4 shows the closed multi-station queueing network model (QNM) of a multi-tier application. Each tier is modeled as a multi-station queueing center, with the number of stations being the tier's total number of

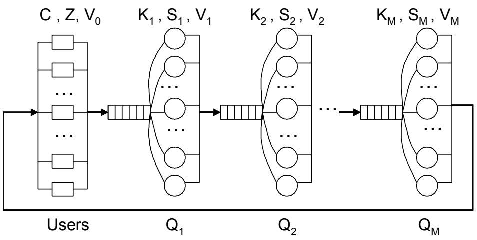


Figure 4. Closed multi-station queueing network model

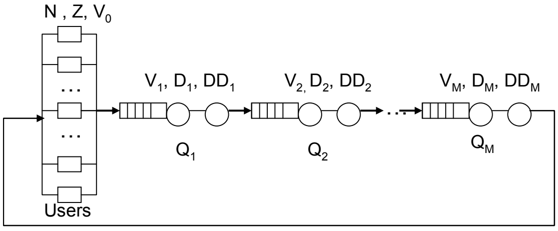


Figure 5. Approximate model for MVA analysis

servers and each user is a delay center with service time equaling think time Z. We use K_i to denote the number of servers at tier i. Similarly, the service demand at a server of tier i is denoted by D_i.

Given any closed workload in terms of number of users C and the transaction mix percentage $\pi = (p_i, p_2 \dots p_K)$, the average service demand of the workload D can be computed from the application profile as the weight average of the service demand of each individual transaction $D = \sum_{i=1}^{N} p_i \bullet D_i$.

Given the parameters $\{C, Z, M, K_i, D_i\}$, the proposed closed queueing network model can be solved analytically to predict the performance of the underlying system. For example, an efficient algorithm such as the Mean-Value Analysis (MVA) can be used to evaluate the closed queueing network models with exact solutions [5]. MVA algorithm is iterative. It begins from the initial conditions when the system population is 1 and derives the performance when the population is i from the performance with system population of (i-1), as follows

$$R_k(i) = \begin{cases} D_k & \text{delay resource} \\ D_k \times (1 + Q_k(i-1)) & \text{queueing resource} \end{cases}$$

$$X(i) = \frac{i}{\sum_{k=1}^{K} R_k(i)}$$

$$Q_k(i) = X \times R_k(i)$$

where $R_k(i)$ is the mean response time (mean residence time) at server k when system population is i; $R_k(i)$ includes both the queueing time and service time; $X(i)$ the total system throughput when system population is i; and $Q_k(i)$ is the average number of customers at server k when system population is i.

Traditional MVA has a limitation that it can only be applied to single-station queues. In our model, each tier is modeled with a multi-station queueing center. To solve this problem, we adopt an approximation proposed by Seidmann et al. [6] to get the approximate solution of performance variables. In this approximation, a queueing center that has m stations and service demand D at each station is replaced by two tandem queues. The first queue being a single-station queue with service demand D/m, and the second queue is a pure delay center, with delay D×(m-1)/m. It has been shown that the error introduced by this approximation is small [7]. By using this approximation, the final queueing network model is shown in Figure 5.

Input: C, $Z, M, K_i, D_i, (i = 1,.. M)$
Output: R, X
//initialization
$R_0 = Z; D_0 = Z; Q_0 = 0;$
for $i = 1$ to M {
  // Tandem approximations for each tier
  $Q_i = 0;$
  $qrD_i = D_i/K_i$; $drD_i = D_i \times (K_i\text{-}1)/K_i$;
}
//introduce C users one by one
for i = 1 to C {
  for $j = 1$ to M {
    $R_j = qrD_j \times (1 + Q_j)$; // queueing resource
    $RR_j = drD_j$; //delay resource
  }
  $$X = \frac{i}{R_0 + \sum_{j=1}^{m} (R_i + RR_i)}$$
  for $j = 1$ to M
    $Q_j = X \times R_j$;
}
$$R = \sum_{i=1}^{M} (R_i + RR_i)$$

Figure 6. Modified MVA algorithm

The modified MVA algorithm used to solve our queueing network is presented in Figure 6. The algorithm takes the following set of parameters of a multi-tier application as inputs:

- *C:* number of users
- *Z:* think time
- *M*: number of tiers
- K_i: number of stations at tier i $(i = 1, \dots, M)$
- D_i: service demand of a server at tier i $(i = 1, \dots, M)$

The MVA algorithm computes the average response time R and throughput X of the application.

4.4 Handling Multi-class Users

There are typically multiple classes of users or sessions in real applications, representing different SLAs (e.g., Gold customers, Sliver customers and Bronze customers) and heterogeneous workloads (e.g., browsing-heavy transactions, purchase-heavy transactions). Constructing multiple-class models for a heterogeneous workload can accurately model heterogeneous workloads and differentiate SLA requirements of different classes. Such classification enables flexible admission control based on the importance of the class, e.g., preferentially scheduling requests from more important classes and dropping less important requests during overload. We extend our model to handle multiple classes of users. Interested readers, please refer to Appendix for the details.

5. DECOMPOSITION

Given an SLO (e.g., response time) and a workload, the goal of decomposition is to determine the design parameters (e.g., number of servers at each tier) to guarantee that the system has enough capacity for processing the specified workload and meeting the proposed SLO. The output of decomposition contains operational policy settings such as

- how many servers are required for each tier
- what's the CPU, Memory, IO utilization of each server

As we discussed before, we generate the profile based on the historical data or benchmarking data with varying workloads. The service demand of each individual transaction type is retrieved from the archive, as shown in Figure 1. Given any workload and a response time requirement, the task of decomposition is then to find the set of model input parameters such as number of servers that satisfy the response time requirement and further derive the resource utilization. Decomposition thus becomes a constraint satisfaction problem. We have developed a simple constraint satisfaction solver to solve this problem. The solver takes performance goal, workload, resource profiles and performance model as inputs and constructs a set of constraint equations. Various constraint satisfaction algorithms, such as linear programming and optimization techniques, are available to solve such problems [21]. Typically, the solution is non-deterministic and the solution space is large. However, for the problems we are studying, the search space is relatively small. For example, if we consider assigning the number of servers at each tier, we can efficiently enumerate the entire solution space to find a solution. Also, we are often interested in finding a single feasible solution (rather than the optimal solution), so we can stop the search once one is found. Other heuristic techniques can also be used during the search. For example, the hint that the response time typically decreases with respect to the increase of allocated resources can also reduce the search space.

One advantage of our approach is that once the profile and model are created, they can be repeatedly used to perform decomposition for different SLOs and workloads. That is, if the response time or workload changes, we only need to resolve the constraint satisfaction problem with the new parameters. Similarly, if the application is deployed to a new environment, we only need to regenerate the profile in that environment using regression analysis. Further, given high-level goals and resource availability, we can apply our decomposition approach for automatic selection of resources and for the generation of sizing specifications that could be used during system deployment.

5.1 Decomposition for open workloads

The performance model for open workload can be represented as follows.

$$RT = \sum_{k=1}^{m} \frac{\sum_{i=1}^{N} \frac{\lambda_i}{\eta_k} \bullet D_{ik} + \sum_{j=1}^{R} \frac{U_{jk}^2}{1 - U_{jk}}}{\sum_{i=1}^{N} \frac{\lambda_i}{\eta_k}} \quad (2)$$

$$U = D_0 + \sum_{i=1}^{N} D_i \bullet \lambda_i / \eta \quad (3)$$

Given an open workload in terms of transaction mix distribution (λ_1, λ_1 … λ_N) and a specified SLO of RT < r, the decomposition problem is to find a set of η_1, η_2, … η_M that satisfy the constraint RT < r as well as determine the resource utilization U_{jk} under the configuration. Other constraints can be added, such as $U_{cpu} < 50\%$, $U_{disk} < 60\%$. To find the solution of the above equations, our current solver simply enumerates all combinations of different number of servers that satisfy the constraint and then chooses the combination such that the number of servers is minimized. Once we get the η_1, η_2, … η_M, the resource utilization can be computed based on equation (3). Implementing a more efficient solving algorithm (e.g., from Zhang et al. [21]) is left for future work.

5.2 Decomposition for closed workloads

For closed workloads, the performance model does not have a closed form (as does the open model), but the model can be conceptually represented as follows.

$$RT = g(M, C, Z, \eta_1, ..., \eta_M, D_1, ..., D_M)$$

where M is the number of tiers, and variables RT and C denote response time and the number of concurrent users respectively. Variables η_j and D_j represents the number of servers and average service demand at tier j respectively. Please see Section 4 for the definitions of the other variables. The average service demand D_j can be estimated using the weighted average resource demand of each transaction type in a user session. That is, given a user session's transaction mix distribution (p_1, p_2, … p_i,…p_k) and the resource demand of each transaction type at the resource T_1: D_1, T_2:D_2, …,T_N:D_N, the average resource demand is estimated as $D = \sum_{i=1}^{N} p_i \bullet D_i$

Given RT < r and a closed workload (in terms of number of users N and the transaction mix distributions $\pi = (p_i, p_2 \ldots p_K)$ of an M-tier application), the decomposition problem is to find a set of η_j (j = 1, …M).

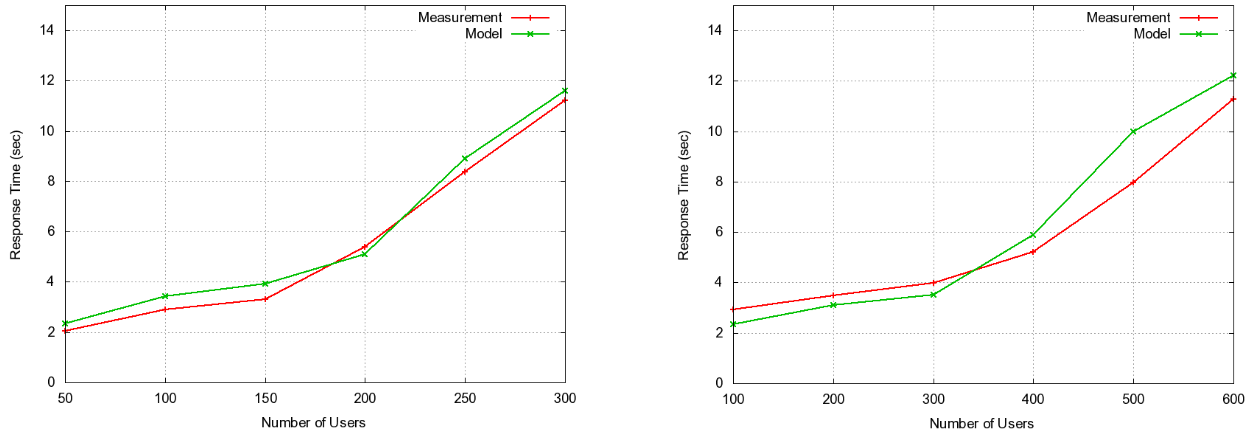
Similar to the decomposition of an open workload, the solver enumerates all combinations of different number of servers that satisfy the constraint and then chooses the combination, such that the number of servers is minimized. Once η_1, η_2, η_M are determined, the resource utilization is derived according to equation (3). Given a new workload, the average service demand is recomputed and the constraint satisfaction problem is solved again, using the new service demand parameters.

6. EXPERIMENT EVALUATION

We evaluated our approach with two applications, the popular RUBiS e-commerce application with synthetic workloads and a real business-critical service with real traces.

6.1 RUBiS Testbed

RUBiS is an eBay-like online auction site developed at Rice University [1]. We use a 3-tier EJB-based implementation of RUBiS consisting of an Apache Web server 2.0, a JBOSS 4.0.2 application server, and a MySQL 5.0 database server, each running on different servers. The RUBiS implementation defines 26 interactions, has 1,000,000 users and 60,000 items. The testbed includes multiple Linux servers. Each server has 2.4 GHz CPU, 4 GB of RAM, and a 1Gb/s Ethernet interface. We developed a workload generator that can produce both open and closed workloads. For open workloads, the workload generator sends requests according to a specified request rate and



(a) One JBOSS Server (b) Two JBOSS Server

Figure 7. Performance with different number of users

transaction mix. For closed workloads, the workload follows a given transition matrix to simulate multiple concurrent users interactions with RUBiS. The workload generator runs on a separate server node from any of the RUBiS systems.

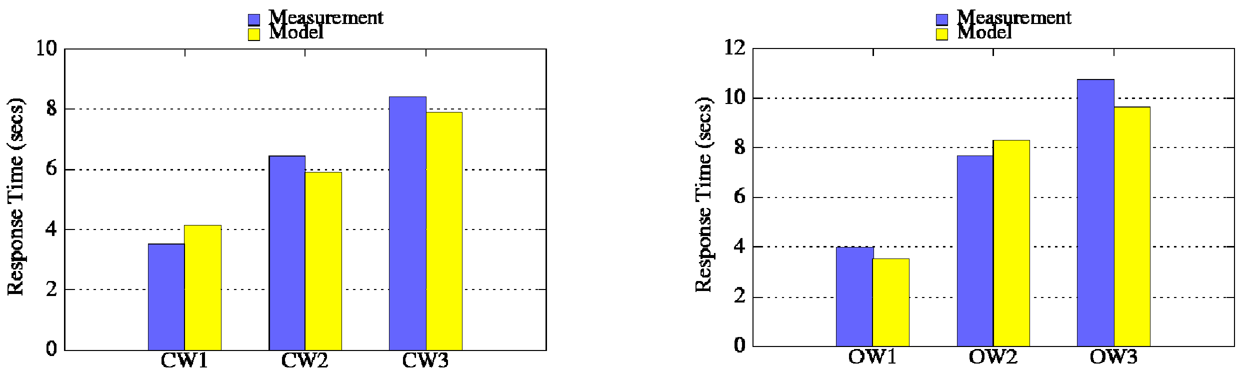
6.1.1 Performance Prediction

To validate the correctness and accuracy of our model, we compare the response times predicted by our model and actual measurements with different workloads under different configurations.

We use the workload generator to produce variable workloads with fluctuations in request rate and transaction mix. Application data is obtained from Apache and JBoss log. System utilization is collected every one minute using the SAR monitor. The data set records two kinds of data about RUBiS, application-level data such as transaction request rate of each transaction type, and system level resource utilization (e.g., CPU utilization). We then apply the regression analysis described in Section 3 to generate the application's resource profile. Given any open or closed workload, we use the resource demand information obtained during profiling as model input parameters, and apply the performance model described in section 4 to derive the response time.

In the first experiment, we change the workload by varying the number of concurrent users generated by the workload generator. Each run lasts 20 minutes, following a 5 minute warm-up period. Figure 7(a) shows the results of the average response times predicted by the model for 50 to 300 concurrent users on our RUBiS testbed. This figure also shows the actual results from this testbed. From the figure we can see that the performance model predicts the performance of RUBiS accurately, as the maximum relative error is less than 15%. In the second experiment, we reconfigure the RUBiS tested with two JBOSS servers and repeated the experiment. The Web server evenly distributes workload among these two JBOSS servers. The results are shown in Figure 7(b). In this case, our model has a maximum relative error of 20%. It is less accurate than single application server configuration due to the error introduced by multi-station queueing model and the load balancer overhead. The above results show that the regression-based profiling and the queuing network model can model the performance behavior of RUBiS application.

In the next set of experiments, we evaluate the effectiveness of our approach for different mixes of browse and bid transactions. First, we define three typical closed workloads of 200 users with different transaction mixes: CW1: browse dominant, CW2: balanced and CW3: bid dominant. For each workload, we use the profile and model to predict the average response time, and then



(a) Closed Workload (b) Open Workload

Figure 8. Performance with different workloads

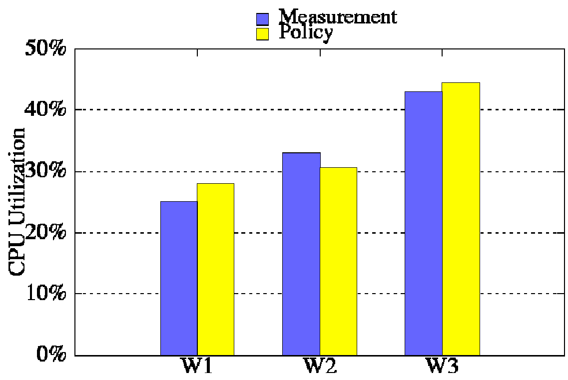


Figure 9. CPU utilization with different workloads

compare the results with the actual performance. The results are depicted in Figure 8(a). The results show that our model can accurately predict the performance for different closed workloads with different transaction mixes. Similarly, we define three typical open workloads with different transaction mixes: OW1, OW2 and OW3 and compare the accuracy of response time predicted by our model for each workloads. The results depicted in Figure 8(b) indicate that our model can also work well with open workloads. These results clearly demonstrate that our model can use the same profiling results (i.e., model input parameters) obtained during profiling to predict the performance of any unforeseen transaction mixes.

We also conducted a similar evaluation of the RUBiS configuration with 2 JBOSS servers. We obtained similar results, and thus do not include the figures here.

6.1.2 Deriving Operational Policies

One of the goals of our SLA decomposition is to derive healthy ranges of system metrics and configure lower level operational policies accordingly. In this set of experiments, we evaluate how well our model can be used to derive such low-level policies given a workload or transaction mix. Resource consumption at the Web tier and database tier are negligible in our testbed, so we focus on the resource utilization of the application server tier only. Given a workload, we derive the CPU utilization as described in Section 4. Figure 9 compares the CPU utilization predicted and measured for three different transaction mixes. As shown in this figure, the maximum relative error is less than 10%. We also have similar results for multi-server RUBiS, which we do not include here.

6.1.3 Decomposition Effectiveness

In this section, we evaluate the effectiveness of our SLA decomposition. Given any workload and SLOs, our decomposition module constructs a set of constraints and then solves the corresponding constraint satisfaction problem. The output of decomposition contains the number of servers required at each tier to meet the response time requirements, as well as the resource utilization of the configuration. In the following experiments, given any SLO in terms of workload and a response time requirement, we generate the number of application servers needed, and predict the average CPU utilization. We then configure RUBiS based on these derived settings. We validate our design by applying the workload, and measuring the actual performance of RUBiS and comparing the results with the SLO.

We also compare the predicted CPU utilization with the actual CPU utilization. A guideline regarding resource utilization is to keep peak utilizations of resources, such as CPU, below 70% [14]. In practice, enterprise system operators are typically even more cautious than this conservative guideline. Hence, we also put additional constraints of CPU utilization to be less than 60% in our evaluation.

Table 2. Decomposition results for closed workload

Input	Output			Measurement	
Workloads and SLOs	Num. of App. Servers	Resp. Time	CPU Utili.	Resp. Time	CPU Utili.
User=100 Browse Intensive Response time<5 sec	1	3.49 s	21.8%	3.03 s	24.5%
User=100 Bidding Intensive Response time< 5 sec	1	4.03 s	35.6%	4.36 s	33.2%
Users=200 Browse Intensive Response time < 5 sec.	1	4.77s	43.2%	4.67 s	47.8%
User=200 Bidding Intensive Response time< 5 sec.	2	4.24 s	37.4%	4.43 s	32.9%

In these experiments, we first consider the high level SLOs in terms of the number of concurrent users, the transaction mix and the average response time. Table 2 summarizes the input and output of decomposition for four different SLOs. The first column shows the input to our decomposition and the second column describes the output of decomposition such as the system design parameter (i.e., number of JBOSS servers) and the healthy range of CPU utilization under the proposed configuration. The measurement column shows the actual measurement of response time and the CPU utilization of the system with the design.

As shown in the first row, for the SLO of *100 users with browse-intensive transaction mix and response time < 5 seconds,* decomposition determines that only one server is required to ensure the SLO and the response time and CPU utilization are 3.49 seconds and 21.8% respectively. The actual measurements of response time and CPU utilization are 3.03 seconds and 24.5%. This shows that the design can meet SLOs and the utilization prediction is close to real system measurement. The second SLO has 100 users but with a different transaction mix (i.e., bidding intensive). We can see from this experiment that the decomposition results are close to the actual measurements. The third input involves 200 concurrent users and browsing intensive transactions, the decomposition result shows that only one server is needed to meet the SLO. The fourth input has 200 users with bidding intensive workload, which is more resource demanding. The decomposition module determines that 2 servers are required to handle the workload and meet the response time requirement. The actual performance shows that the design can meet the requirement and the prediction of response time and CPU utilization are relatively accurate. From the above results, we can see that our decomposition approach can be effectively applied to design and monitor such multi-tier applications with different SLOs.

In order to further check the applicability of our approach, we also apply the decomposition to SLOs involving open workloads. We experimented with four different SLOs. In the experiment, the workload is specified in terms of request rate and transaction mix.

These results are summarized in Table 3. The results show that our approach can also work well with open workloads.

Table 3. Decomposition results for open workload

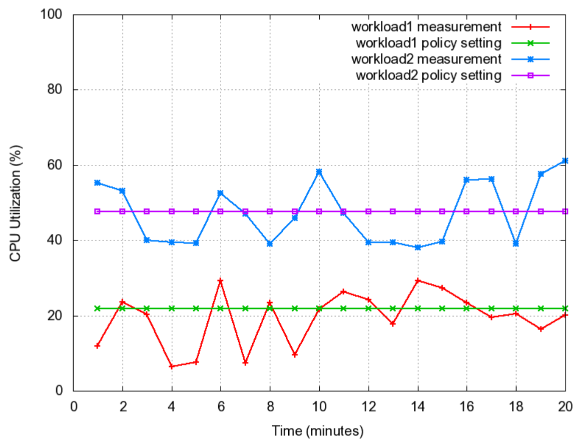
Input	Output			Measurement	
Workloads and SLOs	**Num. of App. Servers**	**Resp. Time**	**CPU Utili.**	**Resp. Time**	**CPU Utili.**
30 reqs/s Browse Intensive Response time<5 sec	1	3.88 s	23.4%	3.67 s	25.1%
30 reqs/s Bidding Intensive Response time< 5 sec	1	4.53 s	37.3%	4.75 s	42.0%
40 reqs/s Browse Intensive Response time < 5 sec.	1	4.47s	40.1%	4.81 s	44.5%
40 reqs/s Bidding Intensive Response time< 5 sec.	2	3.94 s	32.3%	4.33 s	36.7%

6.2 Production Application

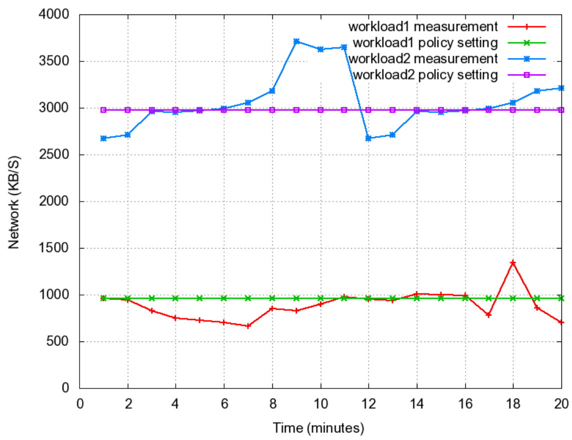
We also evaluate the ability of our decomposition approach to generate low-level resource utilization policies for a real business-critical enterprise application. This service consists of roughly 20 servers and processes tens of millions of application-level transactions per day. The service is CPU and network intensive and its performance is crucial to many other services. In the evaluation, we run the service with a 24 hour request trace from one of the actual servers. As described in Section 3, the profile captures the CPU and network demand for each transaction type. We then extract two typical workloads with different transaction mixes: a lightweight one and a heavyweight one. Given these two workloads, we apply the decomposition approach to generate the CPU and network bounds and further create monitoring policies based on the derived CPU and network bounds. The monitoring policies are according to the utilization predicted by the decomposition model. We apply the workloads and measure the actual CPU and network utilization. The actual CPU resource utilization and the monitoring policies are shown in Figure 10. As shown in the figures, the monitoring policies accurately capture the healthy range of the application for different workloads. These policies can be continuously used to assess how the system is performing and evaluate whether it will violate any of the goals it was designed for. For example, for the first workload, it should warrant CPU Utilization to be around 20%. This metric has to be monitored to make sure that the higher level SLA is met. For example, appropriate actions can be taken when the threshold is violated. This can be defined in an operational policy. In addition, such monitoring policies will also provide a mechanism using which we could predict or even avoid future SLA violations by provisioning the system accordingly in design or capacity planning phase.

7. RELATED WORK

Our previous work proposes an SLA decomposition approach based on profiling and a queueing network model [28]. Although it shares some common features with approach presented in this paper, the basic assumption and modeling techniques are quite different. Our early work focused on managing resource assignment of virtual machines, and the profiling and modeling were relatively simple. The approach presented in this paper aims to develop a practical and advanced model that can be applied to real multi-tier applications with complex, dynamic, non-stationary workloads and varying topologies. Compared to our earlier work, the novel contributions and significant enhancements can be summarized as follows. First, the new performance model is much more advanced and it models multi-tier applications in a much finer-grain manner. Through explicitly modeling per-transaction resource demand, the new approach can handle any unforeseen workloads with different transaction mixes. This is very important improvement since workloads in real production applications are typically non-stationary [25]. Second, our new approach is non-intrusive. The profiling in our early work requires significant efforts to instrument the system and conduct controlled benchmarking in order to collect monitoring data, while our new approach can perform profiling from readily available monitoring data. Third, by defining the workload as transaction mix and introducing open queueing and closed queuing models, our approach can handle both open and closed workloads in a consistent manner. Fourth, our model can directly derive the healthy range of low level system metrics and further develop monitoring policies from the profiles. We also increased the



(a) CPU Utilization



(b) Network Usage

Figure 10. Monitoring Policies

number of system metrics considered. Finally, we evaluate our approach with a real production application. It has been shown that the approach works well for realistic workload under normal system load.

A lot of research efforts have been undertaken to develop queueing models for multi-tier business applications. Many such models concern single-tier Internet applications, e.g., single-tier web servers [9, 10, 11, 12]. A few recent efforts have extended single-tier models to multi-tier applications [16, 17, 19]. The most recent and accurate performance model for multi-tier applications is proposed by Urgaonkar et al. [17]. Similar to our closed workload model, their model uses a closed queueing network model and Mean Value Analysis (MVA) algorithm for predicating performance of multi-tier applications. Despite the similarities, our model is different from theirs in the following aspects. First, we explicitly model the service demand or resource demand per transaction type. As a result, given any unforeseen transaction mix, our model can derive the aggregated service demand for that type of workload and use it as model input parameters to predict the performance. Urgaonkar et al. estimate model parameters for certain transaction mixes and hence the results are expected to work for the similar types of transaction mix. Once the transaction mix changes, a set of new parameters has to be obtained. Second, their model parameter estimation requires detailed service demand information that is not readily available from traditional monitoring, e.g., instrumentation is required to collect data from MySQL database server while our profiling requires only system level utilization and application transaction statistics which are generally available from any applications. Considering the unpredictability and the large number of transaction mixes in real applications, we expect their approach is more difficult to apply in practice. Third, we use a multi-station queue while their model assumes a single-station queue. The use of multi-station queues also enables us to model a multi-server tier the same way as a single server tier. The approximate MVA algorithm for a multi-station queue is more accurate than simply adjusting the total workload. Fourth, Urgaoknar et al. take into account congestion effects in their model. We have not addressed that yet partly because it is undesirable for a production application to operate under high system load. Though our model can be adjusted to handle imbalance across tier replicas based on queueing theory, we have not explored these areas yet. Finally we also report our validation results on both RUBiS testbed and a real production application with non-stationary workloads while their evaluation is based on RUBiS testbed with a stationary synthetic workload.

Kelly et al. present an approach to predicting performance as a function of workload [26]. Their model explicitly models non-stationary transaction mix and shares some features with our open workload model. Both models employ an open queueing network model. The main difference is that they model the aggregated service time across all tiers, while our model associates service times at a per-tier level. Their model works well for the purpose of performance prediction, but for the purpose of decomposition, necessary to model the application in a finer-grained manner. Another improvement from our open workload model is that we generalize M/M/1 queue to K M/M/1 queues and hence can handle general multi-server configuration in typical multi-tier applications. This extension is required by the decomposition. In addition, our model explicitly models the visit rate at each tier, and hence can handle non-uniform requests distribution across tiers.

The regression-based profiling presented by Zhang et al. [27] is similar to our profiling, but we model multi-tier applications at a much finer-granularity. Schroeder et al. considered open and closed workloads as part of a separate study [25], but their focus is on the workloads themselves. Zhang et al. present a nonlinear integer optimization model for determining the number of machines at each tier in a multi-tier server network [20]. The techniques to determine the bounds can be applied to solve our constraint optimization problem. Sharc dynamically allocates resources based on past usage [18]. The focus is mainly in building effective resource control mechanisms for large clusters. Gupta et al. address the system behavior with fluctuating loads [30]. Squillante et al. studied the complex behaviors in high volume Web sites that exhibit strong dependence structures and demonstrated that the dependence structure can be accurately represented by an arrival process with strong correlations [31].

8. CONCLUSION AND FUTURE WORK

One of the most important tasks towards SLA management is to automate the process of designing and monitoring systems for meeting higher level business goals. It is an intriguing but difficult task due to the complexity and dynamism inherent in today's multi-tier applications. In this paper, we propose a systematic and non-intrusive approach that combines performance modeling with performance profiling to solve this problem by translating high-level goals to more manageable low-level sub-goals. These sub-goals feature several low-level system metrics and application level attributes which are used for creating, designing, and monitoring the application to meet high level SLAs. Compared with existing approaches, our performance modeling and SLA decomposition have several desirable features. Our approach can deal with dynamically changing workloads in terms of change in both request volume and transaction mix. Our approach is non-intrusive in the sense that it requires no instrumentation and the data used in our approach is readily available from standard system and application monitoring. Our approach can process both request-based and session-based workloads.

In the future, we will look at SLA management that takes into account multiple components: complex service infrastructures, multiple quality of service metrics (e.g.,, performance, availability, and power), the impact of constraints imposed by security and resource consumption, as well as conflicting interests from the multiple parties involved (infrastructure provider, service provider, and end-user). We are also interested in investigating the dynamic selection of an appropriate workload and performance model for real semi-open workload.

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APPENDIX Handling Multi-class Users

Let C be the number of classes. Each class C has a fixed number of users N_C with think time Z_c. Let $S_{c,i}$ denote the service time of class C_i at tier i and $V_{c,i}$ denote request rate of class C_i at tier i. The multi classes closed queueing network can be analytically solved by using an extension of the single class MVA algorithm. The extended algorithm is presented in the Figure on the right. The algorithm takes the following set parameters of as inputs and computes the per-class response time R_c and throughput X_c.

C: number of classes

N_c: number of users of class c; (c = 1,…,C)

Z_c: think time of class c; (c=1,…,C)

M: number of tiers

K_i: number of stations at tier i (i = 1,…,M)

$S_{c,i}$: service time of class c at tier i (c = 1,…,C i = 1… M)

$V_{c,i}$: mean request rate of tier i (c = 1, …, C i = 1… M)

The complexity of the algorithm is $CM\prod_{c=1}^{C}(N_c+1)$ where CM is the complexity of the computations for one feasible population, and the product term is the total number of feasible populations. The space complexity is $M\prod_{c=1}^{C}(N_c+1)$. The time and space complexities are proportional to the number of feasible populations and hence it can require excessive time and space for the large number of classes or large number of users. Approximation algorithms are often used in practice. It has been demonstrated that approximate algorithms are quite accurate and require much less storage than the exact algorithm. The saving in time is considerable though it is harder to quantify because of the iterative nature of the approximation algorithms.

Input: $N_c, Z_c, M, K_i, S_{c,i}, V_{c,i}$ $(i = 1,.. M, c = 1... C)$
Output: R_c, X_c $(c = 1, ... C)$
//initialization
$Q_0 = 0;$
$N = \sum_{i=1}^{c} N_c$
for $i = 1$ to M $Q_i = 0;$
for $c = 1$ to C $\{R_{c,0} = Z_c; D_{c,0} = Z_c;\}$

for $c = 1$ to C
  for $i = 1$ to M {
    / / Tandem approximations for each tier
    $D_{c,i} = (S_{c,i} * V_{c,i}) / V_{i,0};$
    $qrD_{c,i} = D_{c,i}/K_i$; $drD_{c,i} = D_{c,i} \times (K_i-1)/K_i$;
  }

for $n = 1$ to N
  for *each feasible population with total number of* $n = (n_1, ...n_C)$
  {
    for $c = 1$ to C {
      for $i = 1$ to M {
        $R_{c,i} = qrD_{c,i} \times (1 + Q_i)$; // queueing resource
        $RR_{c,i} = drD_{c,i}$; //delay resource
      }

    for $c = 1$ to C
    $$X_c = \frac{n_c}{R_{c,o} + \sum_{i=1}^{M}(R_{c,i} + RR_{c,i})}$$
    for $i = 1$ to M
    $$Q_i = \sum_{c=1}^{C} X_c R_{c,i}$$
  }
  for $c = 1$ to C
  $$Rc = \sum_{i=1}^{M}(R_{c,i} + RR_{c,i})$$

Multi-class MVA algorithm