Continuous resource monitoring for self-predicting DBMS

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Abstract

Administration tasks increasingly dominate the total cost of ownership of database management systems. A key task, and a very difficult one for an administrator, is to justify upgrades of CPU, memory and storage resources with quantitative predictions of the expected improvement in workload performance. Current database systems are not designed with such prediction in mind and hence offer only limited help to the administrator. This paper proposes changes to database system design that enable a Resource Advisor *to answer "what-if" questions about resource upgrades. A prototype Resource Advisor built to work with a commercial DBMS shows the efficacy of our approach in predicting the effect of upgrading a key resource — buffer pool size — on OLTP workloads in a highly concurrent system.*

1 Introduction

Administering database systems is a complex and increasingly expensive task, and there is a pressing need for greater automation in this area [7, 13]. A key aspect of DBMS administration is *resource provisioning*: given a hardware budget, an administrator must decide whether and in what proportion to invest in faster processors, additional memory, or larger and faster disks. DBMS running transactional workloads serve as back ends to a variety of enterprises such as e-commerce, banking, and travel reservation systems, essentially determining the application's response time [19]. Accurate database resource provisioning is thus vital to ensuring quality of service in these enterprises.

Such enterprises typically hire human experts who use experience and rules of thumb [12] to decide whether acquiring more resources will improve performance. The cost of hiring skilled DBAs for resource provisioning decisions is high for large enterprises and practically prohibitive for the large number of small businesses using DBMS as back ends. Even experts find it difficult to *quantify* the expected benefit of a resource upgrade, an especially challenging task for highly concurrent OLTP (On-Line Transaction Processing) workloads whose behavior at any point in time is the combined effect of many concurrent transactions. The net effect is that DBMS are often over-provisioned.

In this paper we argue that the DBMS itself is in the best position to answer "what-if" questions from administrators about its resources. In addition to sharing the resources fairly among workloads, the DBMS should be proactive in suggesting resource upgrades and predicting their effect on both aggregate and per-request performance. To gain insights on required system changes that will enable such self-predictability, we have build a prototype *Resource Advisor* for a recent unreleased version of Microsoft's SQL Server DBMS.

The Resource Advisor aids administrators in making resource upgrade decisions by answering what-if questions about hypothetical resource upgrades such as "How would performance be affected if I doubled the amount of memory on this server?" with *quantitative* answers: "throughput will increase by 40%, the response time of 'new order' type transactions will decrease by 80%, and the bottleneck will move from the storage system to the CPU". Although many aspects of database performance have been individually studied in great detail, we believe this is the first attempt to automatically answer such high-level questions through an architecture that integrates online, end-to-end, live system tracing with hardware resource models and performance prediction.

One resource of great interest for DBMS administrators is main memory. The size of the buffer pool for caching table and index data retrieved from disk has traditionally been one of the most important performance limiting factors [5, 9, 11]. Its effect on performance, however, is inherently workload-specific and non-linear, and hard to predict using rules of thumb. Although the Resource Advisor is designed to answer "what-if" questions about all three hardware resources (CPU, storage, and main memory) relevant to a DBMS, our prototype implementation and evaluation focus on the main memory buffer pool as the variable resource.

The contributions of this paper are as follows:

- We demonstrate the feasibility of answering "what-if" questions through a prototype implementation and evaluation of a Resource Advisor for a commercial DBMS.
- We present a modular architecture for the Resource Advisor, and identify the key components required for effective self-prediction: low-level instrumentation, end-to-end tracing, and parametrized models of hardware resources.
- We demonstrate the additional benefits of our end-to-end tracing technique in providing detailed information for visualization and understanding of system performance.

Our design and implementation are validated through detailed experiments showing that the Resource Advisor accurately predicts changes in OLTP workload performance across large changes in available main memory resources. When available memory is doubled, for instance, the Resource Advisor predicts the resulting throughput to within 7% or better. The Resource Advisor also correctly tracks the trend in transaction response time across a range of memory sizes spanning more than an order of magnitude.

The remainder of this paper is organized as follows. Section 2 provides background and motivates our approach. Section 3 describes the instrumentation required for a DBMS to support self-prediction, as well as the range of performance visualizations enabled by such instrumentation. Section 4 describes the predictive models that process traces from the instrumented DBMS to generate answers to "what-if" questions. Section 5 presents an evaluation of a prototype Resource Advisor with a real commercial DBMS. Section 6 discusses related work, and Section 7 concludes with a summary of our contributions and directions for future work.

2 Motivation and design

Large commercial databases are complex systems that depend on several physical resources such as the back end storage system, volatile main memory and CPUs. A database administrator (DBA) must decide on a good initial configuration of these resources, and then continuously monitor the system for new bottlenecks and changes in workload. There are two nightmare scenarios that every DBA faces. First, when clients complain that their workload performance does not meet service-level agreements, she needs to pinpoint the source of the problem. Second, a fixed budget is allocated to buying new hardware during periodic system upgrades. Which resources should the DBA upgrade and how can she quantify the effect on workload performance? From talking to administrators of real database systems, it is clear that they do not have the right tools to handle these scenarios.

The most common solution — over-provisioning all the resources that might impact performance — is wasteful and can even be prohibitively expensive. A second approach is to monitor performance using the aggregate counters provided by most commercial DBMS [14, 21, 22]. Such per-resource counters provide a narrow view of the system and do not identify the global bottlenecks. (If the observed disk queues are long, should we buy more memory or faster disks?) Additionally, aggregate statistics do not offer any insights into response time, since they do not distinguish between background and foreground ("critical-path") resource usage. Finally, to determine the effect of a change in the available resources the DBA must still constructively interpret the performance implications of 400+ counters.

The challenge here is to predict the performance impact of additional resources, in order to invest in resources for optimal price/performance. In other words, the DBA must be able to answer "what-if" questions: given observations of the system with one set of resources, to predict performance with another, hypothetical set of resources. The goal of the Resource Advisor is to provide administrators with automated answers to such "what-if" questions, for example "how will my workload perform if I double the current memory?" In addition to point predictions, it should also forecast *trends*: "what curve will response time follow as memory is increased?" In a typical scenario, the Resource Advisor would be part of the DBMS software at the client site. It would run in the background and continuously collect trace information with which it kept up-to-date summaries of workload resource demand based on recent behavior. At any point, the DBA could propose a resource upgrade and receive a quantitative prediction of the expected performance.

An additional goal is to provide detailed information about current system performance. While an inexpert administrator might only wish to know "what will I get if I buy more resources", a more knowledgeable one might wish to know "why do 'new order' type transactions take so long, where is the time going?" The Resource Advisor should capture sufficiently detailed and accurate information about system performance to allow the construction of such "performance views". It is especially important to be able to construct new, previously unanticipated views without recompiling or reinstalling the DBMS.

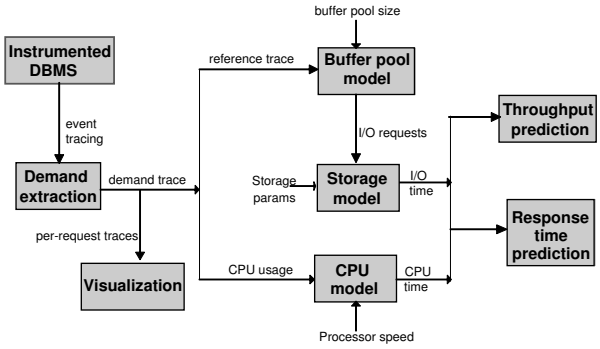


Figure 1. Resource Advisor components.

2.1 Design principles

Our design incorporates several insights we have had into enabling a DBMS to identify resource bottlenecks and predict the impact of upgrading them. First, administrators are usually unable to precisely characterize or model the expected application workload. Additionally, workloads evolve and change over time, causing bottlenecks to shift. This means that resource advice should be based on *continuous monitoring* of a live system running a real application workload.

Second, OLTP performance in particular depends on the interaction between multiple DB components as well as multiple types of transactions executing concurrently. Thus it is insufficient to track aggregate resource utilization statistics: we must *trace* system behavior in sufficient detail to compute the resources used by each transaction, and the order in which they were used, in a highly concurrent execution.

Third, it is essential to separate *demand* from *service*. The former refers to the resource demands placed by the workload on the system, independent of the underlying hardware. The latter refers to the way these resource demands are scheduled by the available hardware resources. To answer "what-if" questions about resource changes, we must distinguish workload characteristics from hardware-dependent measurements.

Finally, we advocate that each individual resource manager in the system be *self-predicting*, with the ability to answer hypothetical questions about their behavior under different resource regimes. For a DBMS, the relevant resource managers are the CPU scheduler, the buffer manager, and the I/O scheduler. The designers of these resource managers are in the best position to incorporate predictive models that correctly reflect their scheduling algorithms, eviction policies, etc. Since current DBMS lack this capability, we demonstrate its feasibility by incorporating resource models for a specific DBMS into the Resource Advisor. Our prototype uses standard analytic and simulation models: our focus is on the Resource Advisor framework rather than specific modeling or simulation techniques.

2.2 Prototype architecture

To illustrate the impact of the above design principles on making a DBMS self-predictive, and to examine the complexity of doing so, we have built a prototype Resource Advisor for SQL Server. Our specific goal was enabling the DBMS to observe the behavior of a live OLTP workload, and predict the results of changing the buffer pool size. This includes identifying the new bottleneck resource (CPU or storage) and predicting the resulting throughput and response time.

Figure 1 shows the high-level architecture of the Resource Advisor. Event traces are generated by the *instrumented DBMS*, and a *demand trace* is extracted which separates out the workload-intrinsic aspects of the resource usage from the hardware-dependent aspects. This resource demand can then be *visualized* in various ways, either in aggregate or by individual transaction, to give a comprehensive view of system performance. The demand trace is also the starting point for answering "what-if" questions. Parametric models of the hardware resources convert the demand trace into predictions of resource usage in a new, hypothetical hardware configuration. These predictions are then used to compute the expected workload throughput and latency.

Note that this architecture is workload-agnostic, i.e. all relevant information about workload behavior is captured in the live system traces, allowing the remaining steps to use generic techniques and models. The design also allows both *online* and *offline* operation, i.e. traces can be consumed live from the running DBMS or captured on disk and analyzed later.

	Event Type	Arguments	Description
Control Flow	*StartRequest*		SQL transaction begins
	EndRequest		SQL transaction ends
	EnterStoredProc	*procname*	Stored procedure invocation
	ExitStoredProc	*procname*	Stored procedure completion
CPU scheduling	*SuspendTask*	*taskid*	Suspend user-level thread
	ResumeTask	*taskid*	Resumes user-level thread
	Thread/CSwitchIn	*cpuid, systid*	Schedule kernel thread
	Thread/CSwitchOut	*cpuid, systid*	Deschedule kernel thread
Buffer pool activity	*BufferGet*	*pageid*	Get reference to a buffer page (blocking)
	BufferAge	*pageid*	Reduce the "heat" of a page
	BufferTouch	*pageid*	Increase the "heat" of a page
	BufferDirty	*pageid*	Mark a page as dirty
	BufferReadAhead	*startpage, numpages*	Prefetch pages (non-blocking)
	BufferEvict	*pageid*	Evict a page to the free pool
	BufferNew	*pageid*	Allocate a new page from the free pool
Disk I/O	*DiskIO*	*startpage, numpages*	Asynchronously read/write pages
	DiskIOComplete	*startpage, numpages*	Signal read/write completion

Table 1. Events used by the Resource Advisor

3 Resource Monitoring

This section describes the instrumentation required by a self-predicting DBMS. It then describes the extraction of aggregate and per-transaction demand traces, and finally the use of demand traces in visualizing workload behavior.

3.1 Instrumentation

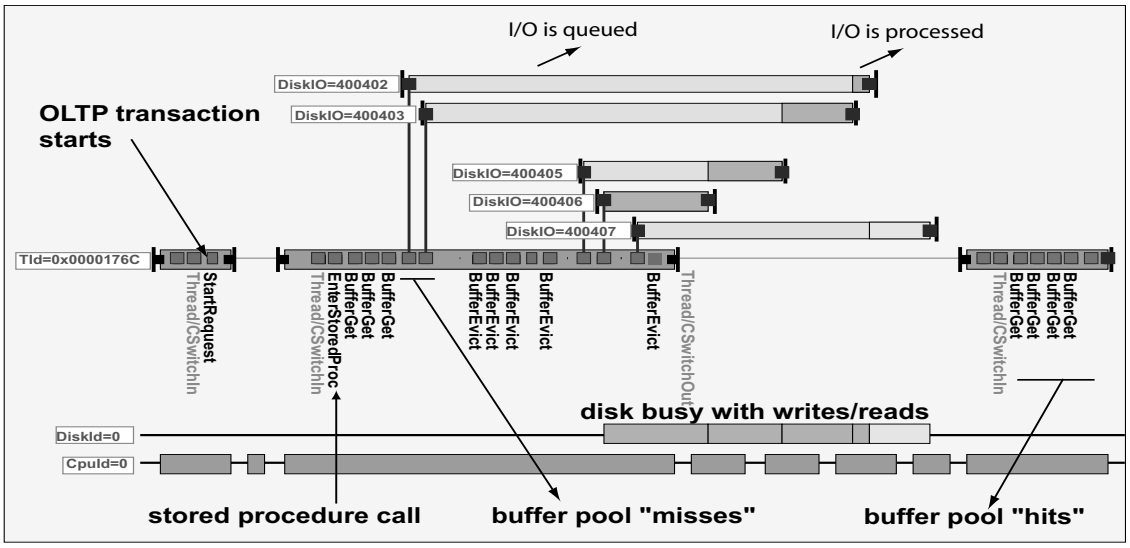
Before making predictions from observations of a live DBMS, we must *instrument* it to provide the information we need: fine-grained, end-to-end traces of transaction resource demands and not just aggregate performance counters. We have instrumented a private copy of the SQL Server source code to track the use of CPU, memory, or I/O resources. Each instrumentation point generates an *event* with associated parameters related to resource usage; these events are then processed in time order by the Resource Advisor components to generate performance predictions. Events are inserted in the DBMS source code as calls to C functions. The implementations of these functions are automatically generated from a high-level definition of the interface between the DBMS and the Resource Advisor.

Currently we trace events relating to transaction control flow, buffer pool activity, disk I/O, and thread scheduling (Table 1). Although the exact interface and instrumentation points depend on the particular DBMS, this list of events represents the information that any DBMS will need to monitor for effective self-prediction. We are extending the event list to include locking activity, which can have a significant impact on response time. This will allow us to extend the Resource Advisor to model the lock "resource".

Each event is automatically annotated with the user and kernel thread IDs and then posted through Event Tracing for Windows (ETW) [20], a low-overhead tracing infrastructure in Windows Server 2003. ETW marks the events with an accurate, high-resolution timestamp derived from the processor cycle counter, orders the events by timestamp, and flushes them in the background.

3.2 Demand trace extraction

A live system trace is the combined effect of workload demand and resource availability. From it, the Resource Advisor extracts a *demand trace* that represents workload behavior in a hardware-independent way. This is then used to represent workload behavior when modeling the effect of changing the hardware resources. The demand trace includes a *buffer reference trace*, which contains the resource-independent aspects of buffer pool activity: demand accesses, readaheads, buffer touches, buffer dirties, and new page creations. It does not include buffer evictions or I/O events, which depend on the buffer pool size. The demand trace also includes the CPU cycles used in executing workload transactions, computed by tracking the active threads within the DBMS using the scheduler context switch events.



The figure shows a timeline view of the resource demands and performance of a single OLTP transaction, extracted from a highly concurrent workload. The view was automatically generated by the Resource Advisor, and only the annotations in large bold font were added by hand. Due to space constraints, we only show an initial portion of the transaction. On the bottom three timelines, we can see when the transaction was being executed by a system thread, when the I/O system was busy processing this transaction's requests, and when the CPU was busy. The "thread" timeline also shows events occurring in the transaction execution path. Some of these events correspond to Disk I/O requests, which are shown in the top 5 timelines.

Figure 2. Timeline view of a single transaction from an OLTP workload

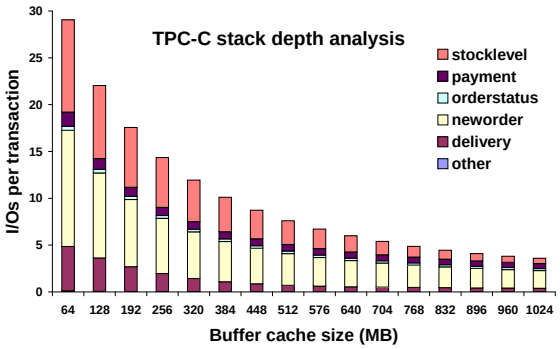


Figure 3. Stack depth visualization

The demand trace contains the interleaved demands of many concurrently executing transactions as well as background tasks such as buffer pool management. From it the Resource Advisor extracts *per-request* demand traces, essential to predicting request response time. Given the thread events and request markers, it ascribes each event and each cycle of computation to exactly one transaction request or background task. It then groups the transaction requests according to their stored procedure invocations: for example, a TPC-C "new order" request invokes `tpcc_neworder` exactly once.

3.3 Virtual performance counters

In addition to its use in answering "what-if" questions, detailed end-to-end tracing provides a wealth of information about current system performance. This information can be represented in a variety of ways to help administrators understand system behavior. In addition to the existing performance counters typically provided by modern DBMS, we can dynamically generate new "virtual" performance counters without any further modification of the DBMS. Once we have correctly instrumented the resource multiplexing points (CPU scheduling, buffer page access, etc.) for each resource of interest, any per-transaction or aggregate performance measure can be derived from the trace data. This flexibility allows an administrator to choose the most appropriate view to understand some aspect of performance. As one example, Figure 3 shows a stack depth analysis [18] of buffer cache locality by transaction type, derived from one of our experimental traces.

In addition to summary views, it is often instructive to examine in detail the behavior of a single transaction, independent of other concurrently executing transactions. Per-request traces allow us to do precisely this. Figure 2 shows an automatically generated "timeline view" of a single "new order" transaction selected from a highly interleaved TPC-C execution.

4 Answering "what-if" questions

The primary function of the Resource Advisor is to answer "what-if" questions about system performance in a hypothetical hardware configuration. In other words, given a workload demand trace, we wish to predict its performance with different resources. In this section we first describe the performance metrics of interest — throughput and latency — and the operational formulas used to predict them. The inputs to these formulas are provided by the resource models, which predict the behavior of the CPU, storage, and buffer pool managers when resources change. We describe in detail the buffer pool and storage models used in the prototype as they are affected by changes in buffer pool size, the resource that we vary in the experimental validation.

4.1 Performance metrics

The *throughput* of a DBMS running some workload is the number of transaction requests satisfied per second. It depends not only on server performance but also on the client request rate, and whether clients operate in an open or closed loop. In a closed-loop workload, each concurrent user has at most one outstanding transaction request at any time. After the transaction is completed, the user waits for some *think time* before issuing the next one. The throughput depends on this think time as well as on server performance. In an open-loop workload, requests are issued independently of the completion of previous requests, and the throughput equals the request rate as long as all resources are underutilized. *Saturation throughput* is the maximum achievable server throughput, i.e. the request rate when either the CPU or the I/O system is fully utilized but not overloaded.

Thus, the interesting workload performance metrics to predict are:

1. closed-loop throughput with a given think time
2. saturation throughput
3. response time

This work is concerned with server performance. Thus, "response time" consists only of the time between the server receiving a transaction request and sending out a response after committing or aborting the transaction. All delays external to the server process — client-side processing, network queuing, etc. — are considered to be part of "think time" from the server's viewpoint.

4.2 Throughput prediction

To predict the throughput of a workload, the Resource Advisor first identifies the bottleneck or throughput-limiting resource. The expected server throughput T will be that of the bottleneck resource, the lowest of:

- $T_{max/io}$: throughput limit imposed by the storage subsystem servicing the I/O request stream from the buffer pool manager.
- $T_{max/CPU}$: throughput limit imposed by the processor executing the workload's computational demands.
- $T_{max/workload}$: throughput limit imposed by client request rate due to "think time" (user think time, client processing time, network delay, etc.)

$T_{max/io}$ is computed as as $\frac{1}{n_{io}t_{io}}$. Here n_{io} is the average number of I/O requests per transaction predicted by the buffer pool model (Section 4.4). t_{io} is the average I/O service time per request predicted by the storage model (Section 4.5).

$T_{max/CPU}$ is computed as $\frac{1}{t_{CPU}}$, where t_{CPU} is the average amount of CPU time used per transaction. The Resource Advisor currently assumes that this is inversely proportional to processor speed and independent of other hardware parameters.

$T_{max/workload}$ for an open-loop workload is its known transaction rate T. For a closed loop workload, it is $\frac{N_{users}}{t_{think}}$, where N_{users} is the number of concurrent users and t_{think} is the mean think time.

4.3 Response-time prediction

Unlike throughput, response time depends not only on overall resource usage but also on the *critical path* resource usage, which is available from our per-request demand traces (Section 3.2). In the general case, predicting response time requires us to solve the hard problem of modeling the interleaved scheduling of multiple concurrent transactions. Here we present a simpler model which predicts response time by scaling the currently observed response time. For an OLTP workload, this gives promising results despite its simplicity.

The Resource Advisor categorizes transactions into types by the stored procedures invoked and analyzes each transaction type separately, as they can have very different response-time characteristics. Depending on the DBMS and workload, many factors can contribute to response time, notably locking [6, 19]. Currently we only predict delays due to waiting/executing on hardware resources, i.e. CPU and I/O.

For each transaction type X, the Resource Advisor computes the critical-path CPU time per transaction and scales it using the CPU model. I/O blocking time is proportional to the number of blocking I/Os per transaction (predicted by the buffer pool model) and to the average I/O response time including queuing delay. Response time is assumed to be inversely proportional to storage system idleness, and storage system utilization proportional to the total amount of I/O traffic. Thus the predicted mean response time for transaction type X

$$t_X = t'_{X/cpu} + b_{X/io} d'_{io} \frac{1 - U'_{io}}{1 - U'_{io} \frac{n_{io}}{n'_{io}}}$$

From the live system trace we can compute $t'_{X/cpu}$, d'_{io}, U'_{io}, and n'_{io}: the mean critical-path computation time for type X, the mean response time per blocking I/O, the I/O subsystem utilization, and the average number of I/Os per transaction across all types. The buffer pool model provides $b_{X/io}$ and n_{io}: the predicted number of blocking I/Os per transaction of type X and the predicted number of I/Os per transaction across all types.

4.4 Buffer pool model

In the above analyses, the throughput and latency predictions depend on the amount of I/O generated per transaction. I/O is generated due to buffer cache misses and dirty page evictions, which depend on the buffer pool size and also on the buffer management strategies used by the DBMS, especially the cache eviction policy [11]. The prototype Resource Advisor uses a simulation model specific to the DBMS under study, which uses a single global buffer cache and an LFU eviction policy. Our model assumes that the sequence of buffer references, as well as memory allocations for purposes other than caching disk pages (temporary objects or working memory), is independent of the underlying buffer pool size. We have confirmed these assumptions through code inspection and experimentation.

The Resource Advisor makes three simplifications in modeling the real buffer manager. First, the simulator only models the I/Os to the main database tables, assuming a configuration where the recovery log is on a separate disk and is not the performance-limiting factor. Second, the simulator ignores the opportunistic write-back of dirty pages by the DBMS, which occurs only when the I/O subsystem is idle and does not affect the analysis of I/O as a performance-limiting factor. Finally, the DBMS replenishes a small free buffer pool in the background whereas the simulator evicts pages strictly on demand, a negligible difference given that the free pool is very small relative to the total memory.

4.5 Storage model

The storage model predicts the performance of the I/O request stream predicted by the buffer pool model. It uses an analytic model [24] based on the Shortest Seek Time First (SSTF) scheduling algorithm used by almost all modern disk device drivers. It assumes that the I/O request stream is random, with little or no spatial locality. This is a good fit for highly concurrent workloads with many independent requests such as OLTP, especially as the buffer cache tends to filter out much of the locality in the access pattern. If data pages are distributed across disks, the Resource Advisor separates out the I/O requests by disk and analyzes each disk individually as a potential bottleneck. It does not currently model more complex storage schemes such as mirroring or RAID.

The SSTF model predicts the mean I/O service time t_{io} as a function of the known disk parameters such as number of cylinders, seek times, etc. and also of the mean I/O request queue length q_{ave}. The queue length is an input to the model and must be predicted, since it can depend on the resource availability. For example, larger buffer pools generate fewer buffer cache misses, which leads to fewer outstanding I/Os per user and hence shorter queues. We use

$$q_{ave} = (N_{users} - N_{cpu} - t_{think} T)(\frac{N_{nonblocking}}{N_{blocking}} + 1)$$

The first term represents the average number of user connections blocked in I/O at any given time, and the second represents the average number of outstanding I/Os for each such connection. N_{users} and t_{think} are the number of user connections and the mean think time, both workload parameters obtainable from the live system trace. N_{cpu} is the expected number of running or runnable transaction threads, which for our non-preemptive CPU scheduler is the number of processors in the system. The ratio $\frac{N_{nonblocking}}{N_{blocking}}$ of non-blocking I/Os (readaheads and writebacks) to blocking I/Os (demand reads) is predicted by the buffer pool model.

These equations give us the I/O service time t_{io} as a function of the transaction rate T. For a closed-loop, I/O-bound workload, the transaction rate in turn is a function of t_{io} (Section 4.2). The Resource Advisor solves the mutual equations numerically using an iterative computation. Section 5 shows that this simple model of queue length, combined with the analytic storage model, accurately tracks the change in I/O subsystem performance due to changing the buffer pool size.

5 Evaluation

In evaluating the Resource Advisor, the high-level question to be answered is:

Given a live system running a workload, can the Resource Advisor efficiently and accurately predict the performance of the same workload with different resources?

In this evaluation, we answer this question for an OLTP workload with the varying resource being buffer pool size, i.e. memory availability. We break down our earlier question into four sub-questions, and answer each in turn:

- For a closed-loop workload, can the Resource Advisor predict throughput at different memory sizes?
- Given a non-saturation workload, can it predict the saturation throughput at different memory sizes?
- Given a non-saturation workload, can it predict the response time at different memory sizes?
- What are the runtime overheads and other costs of deploying the Resource Advisor?

5.1 Workloads and experimental setup

Our evaluation uses two variants of a TPC-C workload, which differ only in the transaction request rate:

- SAT is a closed-loop saturation workload. Each user operates in a closed loop with near-zero think time, placing the server under heavy load.
- OPEN is an open-loop non-saturation workload with a low, constant transaction rate such that the server always has significant amounts of idle time.

All our experiments were conducted with a single instance of SQL Server running on Windows Server 2003 on a single 2.7 GHz Intel Xeon processor. The 10GB database is stored on a single 80 GB Western Digital WDC800JB disk. To avoid contention with the database disk, the transaction log and the event trace log are directed to two additional disks. Our aim here is not to obtain optimal performance from the DBMS server, but to predict the change in performance when resources change. Thus, we opted for simplicity rather than careful tuning of the hardware and database configuration.

Our stress client simulates 200 independent user connections to the server, runs on a single 2.8 GHz Intel Pentium processor, and is connected to the server by a 100 Mbps ethernet switch. Each workload run consists of at least 5000 transactions and is preceded by a warm-up phase of at least 30000 transactions. Each run is repeated on five different server memory configurations, with buffer pool sizes of 64 MB, 128 MB, 256 MB, 512 MB, and 1024 MB. The CPU and disks were unchanged in all configurations.

The aim of each experiment is to validate the Resource Advisor's answer to a "what-if" question against the measured result of carrying out the hypothetical change. Of the many "what-if" questions a DB administrator might ask, we chose two typical ones related to buffer pool size:

- What will the performance be if I double the buffer pool size?
- What is the trend as I further increase the buffer pool size?

To answer these questions, we show for each experiment two predictions:

- DOUBLE is the predicted performance when the buffer pool size is doubled. It predicts the performance at 128 MB from the trace at 64 MB, at 256 MB from 128 MB, etc.
- TREND predicts performance over the entire range of buffer pool sizes, based on traces from the lowest-memory configuration (64 MB).

We expect DOUBLE to give us accurate point predictions and TREND to correctly track the shape of the memory-performance trade-off curve.

The Resource Advisor can be used either online or offline; in this evaluation, for control and repeatability, the live system traces are logged to disk and prediction is done offline.

5.2 Closed-loop throughput prediction

This experiment evaluates the accuracy of DOUBLE and TREND in predicting the throughput of SAT. We evaluate the accuracy of each individual prediction component as well as the final result. The results are based on 5 identical runs at each configuration, showing the mean and standard deviation of both the measured and the predicted values.

Our first step is to evaluate the accuracy of the buffer pool model. The predicted value is the number of I/Os generated per transaction, which determines the I/O-bound throughput $T_{max/io}$. Figure 4 shows the predicted and actual I/Os per transaction. Figure 5 then shows how well the storage model predicts the I/O service time. Note that our model correctly tracks the slight increase in service time due to decreasing queue lengths.

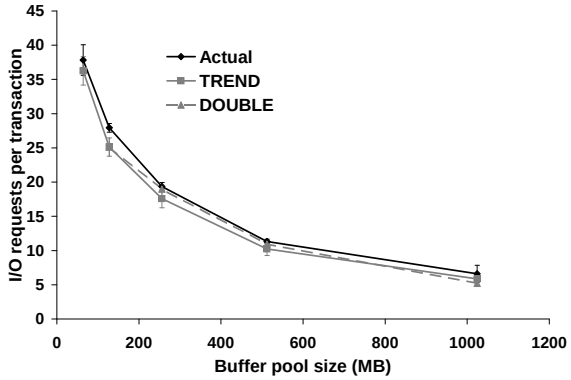


Figure 4. I/Os per transaction for SAT

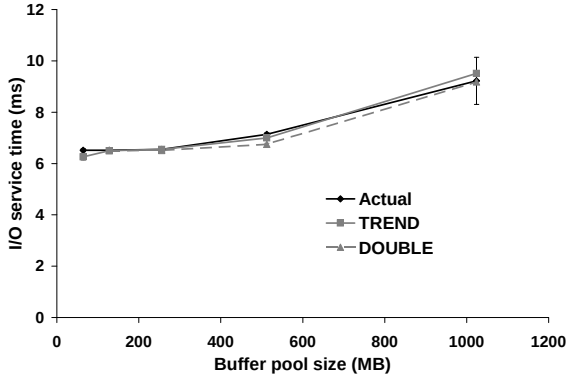


Figure 5. I/O service time for SAT

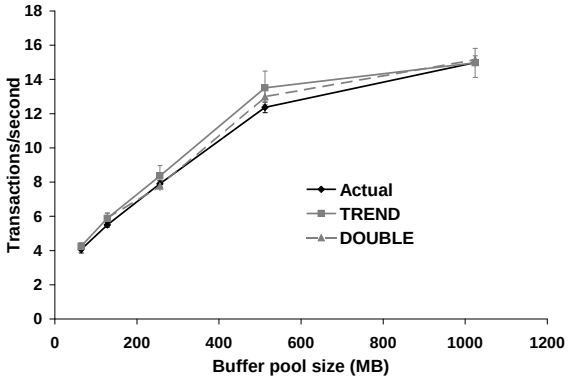


Figure 6. Throughput of SAT

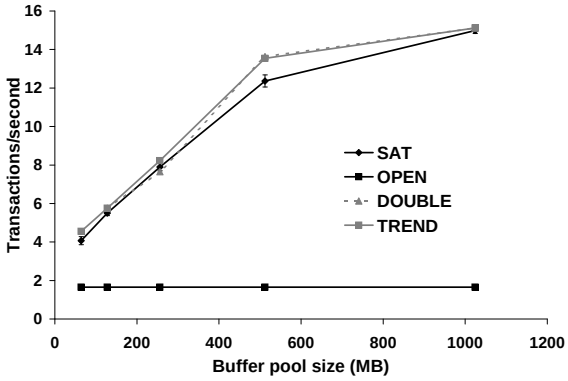


Figure 7. Throughput of SAT (from OPEN)

Given the I/O request stream and service time, the Resource Advisor predicts throughput using the analysis of Section 4.2. Figure 6 shows the accuracy of this prediction. Note that throughput was I/O-bound at all buffer pool sizes except at 1024 MB, when it becomes client-bound, i.e. limited by workload think time. In all cases, the predictor correctly identifies the bottleneck, and we see that TREND tracks the performance curve, while DOUBLE predicts throughput to within 7% or better.

5.3 Saturation throughput prediction

The previous experiment showed that that the Resource Advisor can predict throughput across changes in buffer pool size. Often we also want to predict the effect of changes in *request rate*. For example, we might want to know the maximum or saturation throughput even if the server is not currently saturated. To test this predictive capability, we fed the Resource Advisor a trace from a system running the low-load OPEN workload, and applied the throughput analysis using the previously measured think times of SAT to predict the closed-loop throughput of SAT. This experiment validates the following capabilities of the Resource Advisor:

- *Predicting saturation throughput*: as SAT is a saturation workload in all but the 1024 MB case, correctly predicting its throughput corresponds to correctly predicting saturation throughput. At 1024 MB, correctly predicting SAT's throughput corresponds to correctly identifying that the bottleneck has shifted outside the server.
- *Predicting across rate changes*: SAT and OPEN have very different transaction rates, and in fact different rate models (closed vs. open). Thus predicting the performance of one by observing the other will show that the throughput prediction can track changes in transaction rate as well as buffer pool size.
- *Demand extraction*: the throughput prediction is based on the assumption that the demand trace captures all relevant features of the workload and is independent of server load. This assumption is validated by using the demand trace of OPEN to predict the performance under the very different load regime of SAT.

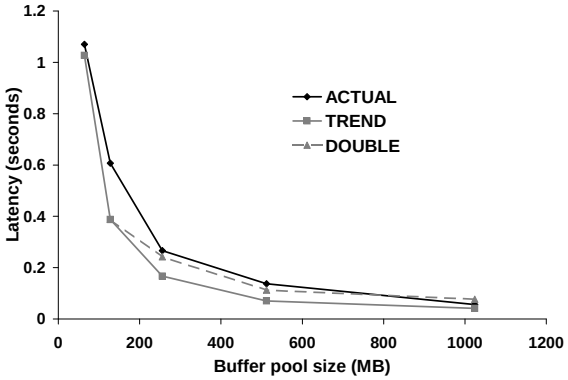


Figure 8. Response time in OPEN

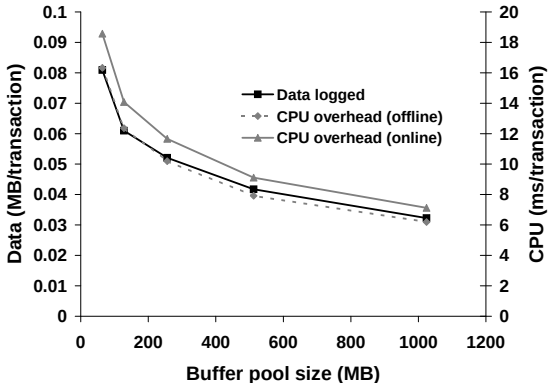


Figure 9. Overhead of event logging

Figure 7 shows the measured throughput of SAT, the DOUBLE and TREND predictions based on a single run of OPEN, and the throughput of OPEN itself. Although SAT and OPEN have completely different throughput trends, the Resource Advisor correctly infers the former by observing the latter: DOUBLE predicts the saturated throughput to within 10% or better and correctly identifies the client as the bottleneck for the 1024 MB case.

5.4 Open-loop response time prediction

Recall from Section 4.3 that the Resource Advisor groups transactions by type. This lets us measure and predict response time by transaction type, since different transaction types have very different critical paths. We predicted the effect on response time of doubling memory for each of the five TPC-C transaction types, in each of four memory configurations. The prediction error varies from 33%–68%. Although this appears large, it is important to note that the underlying variation in response time is also large. In 19 of the 20 cases, prediction error was smaller than the observed standard deviation in latency.

The error is also small compared to the change in response time as memory size is increased. Across the full range of memory sizes measured, response time of all five transaction type changes by more than an order of magnitude. Our predictions accurately follow this *trend* for all five transaction types. Figure 8 shows this result graphically for the "new order" type.

Our results show that the response time model effectively predicts the shape of the memory-response time trade-off curve, and that the point prediction errors are not large compared to the inherent variation in response times. The large variance also indicates that there is little room for further improvement in predicting the mean response time. Instead, the focus should be on predicting the frequency distribution of response times.

5.5 Overheads

Figure 9 shows the runtime overheads of the Resource Advisor: the amount of trace data generated and the CPU consumed per transaction. The overhead per transaction is higher at lower buffer pool sizes: there are more I/O events to process, as well as more background events since transaction execution times are lengthened.

The worst-case CPU overhead is 6.2%, for an unoptimized C# implementation of the Resource Advisor running online. With offline operation, this is reduced to 1.2% for tracing and logging. The trace data rate is a modest 0.44 MB/s in the worst case, whether for online consumption or logging to disk. These overheads could be reduced further with an optimized implementation of the Resource Advisor, and by running it periodically rather than continuously.

A potential concern with self-prediction is the amount of effort required to add it to an existing DBMS. Although we advocate that future DBMS designs incorporate self-prediction as a goal from the beginning, our experience is that this capability can also be added to legacy code with a modest amount of work. Instrumentation of the DBMS required only 189 additional lines of code in 6 source files; it could also be achieved without any source modification by using binary rewriting techniques [3, 8]. The rest of the Resource Advisor runs as a stand-alone program, and is also modest in size: 1150 lines of code.

6 Related work

Much research has identified buffer memory as a key resource for database throughput and response time [9, 11] and proposed various techniques to optimize or adapt memory usage: for example, by dynamically limiting the working memory allocated per query [5]. The Resource Advisor complements this work by predicting the behavior of the buffer manager at different memory sizes, given traces of the memory allocation and buffer references at higher levels.

The technique used by our buffer model — trace-based simulation — is an old and well-studied idea [10, 18]. An alternative approach is to model the cache hit ratio of a specific workload such as TPC-C as a function of buffer size [15, 25]. Although we use a TPC-C like workload in our evaluation, the Resource Advisor itself is workload-agnostic, relying on live system traces to capture the characteristics of the workload. It is thus usable by DBAs with little or no understanding of workload characteristics.

Several studies have proposed detailed cost models of CPU usage and of the processor cache hierarchy [2, 4, 17]. Others have developed models of storage device performance [24, 26]. The novelty of our contribution lies in integrating these approaches into a broader mechanism to answer "what-if" questions about hypothetical hardware changes, and in demonstrating the feasibility of answering these questions online for a live system.

As in Magpie [3] and Pinpoint [8], a key feature of the Resource Advisor is the use of detailed, low-overhead, end-to-end event tracing. Magpie and Pinpoint, however, use the traces for workload modeling and anomaly detection in web servers, whereas the Resource Advisor uses it to predict performance for capacity planning in DB applications.

Finally, resource provisioning is only one of many database configuration and maintenance tasks. Orthogonally to our work, database research has recently focused on automated physical database design tools to reduce manual intervention and maximize performance. The Database Tuning Advisor [1] and DB2 Advisor [16] suggest the most appropriate set of indexes and materialized views as well as the best physical layout of tables, while AutoPart [23] automates database schema design using data partitioning on large-scale datasets.

7 Conclusion

This paper presented a design and implementation for a database *Resource Advisor* that predicts the impact of changing resource availability on workload performance. The Resource Advisor is based on fine-grained, low-overhead tracing; per-request demand extraction; and simple, lightweight, workload-agnostic resource and performance models.

Our primary contribution is to demonstrate that the Resource Advisor can accurately answer "what-if" questions about hypothetical resource changes for a live system: the key requirement for automating decisions on resource upgrades or reprovisioning. We validated this claim by predicting the throughput and response time of an OLTP workload as a function of buffer pool size. Our second contribution is a modular architecture where each analysis and modeling component can be separately replaced or extended. Finally, we demonstrated the value of end-to-end request tracing both in response time prediction and in performance visualization.

Our short-term goal is to more thoroughly validate the Resource Advisor design with a broader range of workloads and resource models. For example, DSS (Decision Support System) workloads are very different from OLTP workloads in having low concurrency, long-running transactions, and phased behavior. In the medium term, we would like to explore the range of prediction options enabled by detailed, realistic, end-to-end tracing. For example, given per-request traces, we could model not just the mean response time but also the distribution of response times. Additionally, we could answer "what-if" questions about changing the workload transaction mix by sub-sampling a trace with a different workload mix. In the long term, we intend to tackle more challenging aspects of performance prediction, such as the effect of locking on response time, as well as performance in a distributed setting such as a two-tier web service with both database and web servers.

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