Design, Implementation, and Evaluation of a QoS-Aware Real-Time Embedded Database

Woochul Kang, Sang H. Son, *Senior Member, IEEE,* and John A. Stankovic, *Fellow, IEEE*

Abstract—QeDB (**Q**uality-aware real-time **E**mbedded **D**ata**B**ase) is a database for data-intensive real-time applications running on embedded devices. Currently, databases for embedded systems are best effort, providing no guarantees on their timeliness and data freshness. Existing real-time database (RTDB) technology cannot be applied to these embedded databases since it hypothesizes that the main memory of a system is large enough to hold the entire database. This, however, might not be true in data-intensive real-time applications. QeDB uses a novel feedback control scheme to support QoS in such embedded systems without requiring all data to reside in main memory. In particular, our approach is based on simultaneous control of both I/O and CPU resources to guarantee the desired timeliness. Unlike existing work on feedback control of RTDB performance, we implement and evaluate the proposed scheme on a modern embedded device. The experimental results show that our approach supports the desired timeliness of transactions while still maintaining high data freshness compared to baseline approaches.

Index Terms—Real-time database, embedded database, transaction tardiness, sensor data freshness, QoS management, feedback control, Multiple Inputs/ Multiple Outputs (MIMO) control.

1 Introduction

Recent advances in sensor technology and wireless connectivity have paved the way for next generation real-time applications that are highly data-driven, where data represent real-world status [1]. For many of these applications, data from sensors are managed and processed in application-specific embedded systems with certain timing constraints. For example, control units of an automobile collect and process a large volume of real-time data not only from internal sensors and devices [2], but also from external environments such as nearby cars and intelligent roads [3][4]. Another examples are PDAs carried by firefighters for search-and-rescue tasks. These PDAs collect real-time sensor data from both the burning building and other firefighters. They also process the data to check the dynamically changing status of the fire scene and alert in a timely fashion if there is a potential danger to the firefighters. [5][6]. In these applications, ad-hoc management of data can increase the difficulty of development due to ever increasing complexity and size of data. Hence, it is essential to provide a systematic mechanism to manage the data.

An embedded database [7] is an integral part of such applications or application infrastructures. Unlike traditional DBMSs, database functionality is delivered as part of the application or application infrastructure. These databases run with or as part of the applications in embedded systems. Embedded databases provide an organized mechanism to access large volumes of data for applications. Instead of providing full features of traditional DBMSs, such as complex query optimization and handling mechanisms, embedded databases provide minimal functionality such as indexing, concurrency control, logging, and transactional guarantees. Several off-the-shelf embedded databases are available such as Berkeley DB [8], and SQLite [9]. However, these embedded databases are unaware of timing and data freshness requirements, showing poor performance in real-time applications [10].

Achieving timeliness of tasks has been a core research issue in the real-time systems domain, and it has been actively investigated [11][12]. Unfortunately, applying those results to the emerging data-intensive real-time applications and embedded databases has several problems. One main difficulty lies in the inappropriate real-time task model of traditional real-time computing work. In particular, most real-time research has been focused on computation-intensive applications. This work assumes that all data resides in main memory for real-time tasks, which might not be true in data-intensive real-time applications. This assumption has been mainly used to eliminate the highly unpredictable response time of I/O operations to disks.

To address these problems, we have designed and implemented a real-time embedded database (RTEDB), called QeDB (Quality-aware Embedded DataBase). QeDB has been designed particularly for embedded devices for data-intensive applications, where not all the data can be fit into main-memory. For such applications, QeDB provides a storage abstraction layer that virtualizes the underlying storage devices while guaranteeing the desired timeliness of transactions accessing data via the abstraction layer. To the best of our knowledge, this is the first paper on providing Quality-of-Service (QoS) for embedded databases with a real implementation. The contributions of this paper are as follows:

1) **Real-time transaction model for RTEDBs:** In QeDB, a real-time transaction is defined as a real-time task that accesses data through a RTEDB with optional transaction guarantees.

- *W. Kang is with Electronics and Telecommunication Research Institute (ETRI), 138 Gajeongno, Yuseong-gu, Daejon, Korea. E-mail: wchkang@etri.re.kr*
- *S.H. Son, and J.A. Stankovic are with the Department of Computer Science, University of Virginia, 151 Engineer's Way, PO Box 400740, Charlottesville, VA. E-mail: {son,stankovic}@cs.virginia.edu*

For example, real-time transactions of a firefighter's PDA run periodically to retrieve the up-to-date sensor data by issuing requests to the underlying RTEDB and also perform computational tasks such as checking the potential dangers, and finding safe paths. Because real-time transactions consist of both data accesses and computation with the retrieved data, the timeliness of these transactions is determined not only by their computational activities, but also by their I/O activities. Further, our observations show that the response time of a transaction's computational activities is highly affected by its I/O activities, and vice versa. For instance, decreasing the size of buffer cache in RTEDBs increases not only the average I/O response time, but also the CPU load because more frequent buffer management activities, e.g., searching for least-recently-used pages, are required due to low buffer hit ratio. This close interaction between computation load and I/O load implies that the QoS of transactions can be guaranteed only when both I/O and computation are considered simultaneously.

2) **A novel feedback control architecture:** In QeDB, the metrics for QoS are the timeliness of transactions and the freshness of data, which may pose conflicting requirements [13]. QeDB achieves the desired QoS using a novel feedback control technique. Even though feedback control has recently been applied to RTDB to systematically trade data freshness for the timeliness of transactions in the presence of dynamic workloads [14][15], these approaches control a single resource, i.e., CPU load, to achieve the QoS goals. In contrast, QeDB exploits a Multiple Inputs/Multiple Outputs (MIMO) modeling and controller design technique to capture the close interactions of multiple control inputs (CPU load and I/O load) and the multiple system outputs (the timeliness of I/O operations and computation). The MIMO controller adjusts both CPU load and I/O load simultaneously.

3) **Implementation:** Most RTDB work is based on simulation and some assumptions are too rigid to implement. Hence, there were limitations in modeling real system behaviors and workloads. Very little prior work, such as [16][10][17], has evaluated real-time data management techniques in real database systems. QeDB has been implemented by extending Berkeley DB [8], which is a popular open-source embedded database, to support a target QoS. QeDB does not require particular support from underlying operating systems; it relies only on the standard real-time features of POSIX [18].

4) **Evaluation:** QeDB has been implemented and evaluated on a real embedded device with realistic workloads. The evaluation results demonstrate that MIMO control of QoS in QeDB is significantly more effective than the baseline approaches. In particular, QeDB makes a better negotiation between the timeliness of transactions and the freshness of data by providing proper amount of resources in a robust and controlled manner.

The rest of the paper is organized as follows. Section 2 presents the overview of real-time transactions and data model in QeDB. Section 3 describes the QeDB architecture and feedback control procedure. In Section 4, we discuss the details of feedback control mechanism in QeDB. In Section 5, implementation issues are discussed. Section 6 shows the details of the evaluation settings and presents the evaluation results. Related work is presented in Section 6 and Section 7 concludes the paper and discusses future work.

2 Overview of QeDB

2.1 System Model

QeDB targets real-time embedded devices, which have relatively small main memory compared to their secondary storage. Since the capacity of the secondary storage is usually far greater than the size of main memory, databases bigger than the main memory can be used with support from the secondary storage. Figure 1 shows the software stack of an embedded system, which runs a real-time application with support from a RTEDB. A buffer cache is located in main memory, and it is a cache between the slow secondary storage and the CPU. The buffer cache is global, and shared among transactions to reduce the average response time in accessing data. An I/O request from application(s) for a data object incurs I/O operations to the secondary storage only if the data object is not found in the buffer cache.

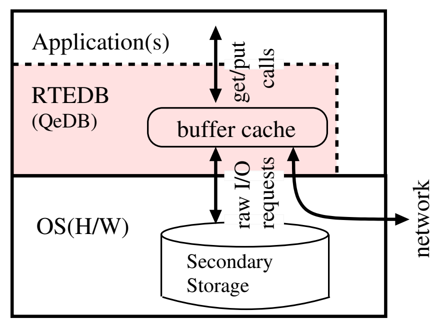


Fig. 1. A real-time application with support from a RT-EDB.

QeDB provides an abstraction layer for real-time applications; it virtualizes the underlying storage devices while guaranteeing the desired timeliness of transactions and data freshness. Data can be accessed transparently regardless of its location; data can be in main memory, secondary storage, or even in somewhere in the network [1].

2.2 Data and Transactions

Unlike traditional DBMSs, QeDB does not support complex query processing of data. Instead, QeDB is a key/value store, which supports efficient and concurrent access to the data[2]. While the interface *put(key* k_1*,value* v*)* is used for the storage of data v with key k_1, the interface *get(key* k_2*)* is used for the retrieval of data with key k_2. Operations *get* and *put* involve mostly I/O operations between the buffer cache and the secondary storage to fetch and flush data. However, they also involve computation such as manipulating the buffer cache, looking up indexes, and locking data and index pages. In

1. Currently, we are developing a network-based transparent data replication layer for QeDB [19].

2. QeDB uses the same data storage and retrieval mechanism of the underlying Berkeley DB without extension.

this paper, *I/O operations* refer to *put* and *get* operations in QeDB, which include not only raw I/O operations to secondary storages, but also computation required for the I/O operations.

Data objects in QeDB can be classified into two classes, temporal and non-temporal data. Temporal data objects are updated periodically by *update transactions*. For example, an update transaction is issued when a new sensor reading becomes available. In contrast to update transactions, *user transactions* may read and modify both temporal and non-temporal data objects. The operations of transactions are hard-coded into the applications, and invoked dynamically at runtime. The characteristics of a transaction, such as its execution time and access pattern, are known at design time. However, the workload and data access pattern of the whole database is unpredictable and changes dynamically because the invocation frequency of each transaction is unknown and multiple transactions execute concurrently. Hence, their response times can be unpredictable. Transactions access data through QeDB and transactional properties such ACID (atomicity, consistency, isolation, and durability) between data accesses are provided if they are specified by the applications.

Program 1 shows an example of a transaction that is invoked periodically in a firefighter's PDA to check the structural integrity of the building[3]. Note that the PDA not only performs I/O operations to get/put data, but also computations that check the integrity of the structure. The logical consistency of the data accesses can be guaranteed by enclosing all or part of the transaction with *begin_transaction* and *commit (or abort)*. However, logical consistency is not required for all transactions and it is application-dependent.

Program 1 A transaction checking the integrity of a structure.

```
trx_check_structure_integrity()
{
   /* A list of keys to sensor data to process */
   DBT key_displacement_sensors={Sen_1,Sen_2,..., Sen_n}

   /* memory to copy in sensor data */
   DBT data_sensors[NUM_SENSORS];

   /* Some computation */
   init();

   /* perform I/Os by reading in data from the DB */
   for (i=0; i< NUM_SENSORS; i++){
       data_sensors[i]= get(key_displacement_sensors[i]);
   }
   /* computation */
   status = analyze_integrity(data_sensors);

   /* another I/O */
   put(key_status, status);
}
```

2.3 Real-Time Transactions

Transactions can be classified as two categories: *real-time transactions* and *non-real-time transactions*. Real-time transactions are real-time tasks, which have deadlines on their completion time, and they have higher priority than non-real-time transactions. For instance, the transaction in Program 1 should report the status of the structural integrity of the burning building within a specified deadline; otherwise, the firefighters may lose a chance to escape from a dangerous place that might collapse. We apply soft deadline semantics, in which transactions still have value even if they miss their deadline. For instance, having a late report on the status of the building is better than having no report due to the abortion of the transaction. Soft deadline semantics have been chosen since most data-intensive real-time applications accessing databases are inherently soft real-time applications. Hard real-time is hard to achieve because of the concurrent data access and the complex interactions that occur, such as database locking. The primary focus of this paper is providing QoS management that can dynamically minimizes the tardiness of these soft real-time transactions at runtime.

3. Some details are not shown for clarity and readability.

3 QoS Management in QeDB

Next, we describe our approach to managing the performance of QeDB in terms of QoS. We define the QoS metrics in Section 3.1. An overview of the feedback control architecture of QeDB is given in Section 3.2.

3.1 QoS Metrics

The goal of the system is to maintain QoS at a certain level. The most common QoS metric in real-time systems is *deadline miss ratio*. The deadlines of transactions are application-specific requirement on the timeliness of the transactions, and the deadline miss ratio indicates the ratio of tardy transactions to the total number of transactions. However, it turns out deadline miss ratio is problematic in RTEDBs because the rate of transaction invocation in embedded databases is very low compared to conventional database systems, which handle thousands of transactions per second. For example, a real-time transaction of a firefighter's PDA, which checks the status of the building, can be invoked on a per-second basis [20]. With such a small number of transactions, the confidence interval of deadline miss ratio can be very wide [21]. This makes the deadline miss ratio not very suitable for a QoS control. Therefore, QeDB controls the QoS based on the average tardiness of the transactions. For each transaction, we define the tardiness by the ratio of response time of the transaction to its respective (relative) deadline.

$$tardiness = \frac{response\ time}{deadline}. \tag{1}$$

Another QoS metric, which may pose conflicting requirements, is data freshness. In RTDBs, validity intervals are used to maintain the temporal consistency between the real-world state and sensor data in the database [15]. A sensor data object O_i is considered fresh, or temporally consistent, if *current time* $- timestamp(O_i) \leq avi(O_i)$, where $avi(O_i)$ is the absolute validity interval of O_i. To support the sensor data freshness for O_i, we set the update period $P_i = 0.5 \times avi(O_i)$ [22]. QeDB supports the desired data freshness in terms of perceived freshness (PF) [15].

$$PF = \frac{N_{fresh}}{N_{accessed}}, \tag{2}$$

where N_{fresh} is the fresh data accessed by real-time transactions, and N_{access} is the total data accessed by real-time transactions. When overloaded, the data freshness could be sacrificed in order to improve the tardiness as long as the data freshness is within the user-specified bounds. This approach is effective if we consider the high update workloads, e.g., sensor data updates during emergency, which may cause significant delays of tasks and transactions.

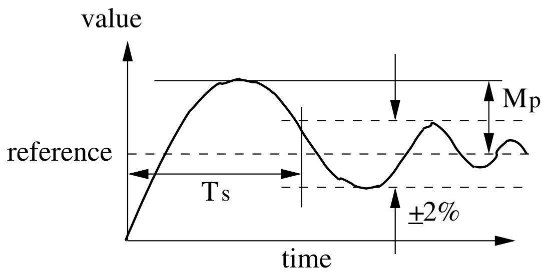


Fig. 2. Definition of settling time (T_s) and overshoot(M_p).

Average performance metrics such as tardiness and data freshness are not sufficient to describe the behavior of dynamic computing systems, in which performance could change significantly in a relatively short time interval [23]. Two performance metrics are introduced from control theory to describe the transient behavior of a computing system (see Figure 2). Maximum overshoot M_p is the worst-case system performance in the transient state and it is given in the percentage to its reference value. Settling time T_s is the time required for the system to reach its steady-sate value, which is usually within $\pm 2\%$ of the reference value.

3.1.1 I/O deadline and CPU deadline

The tardiness of a transaction is determined by the response time of both I/O operations and the computation in the transaction. In particular, in a data-intensive real-time application, the I/O response time is a critical factor. The tardiness of a transaction in Equation 1 tells how much a system is overloaded, but it does not tell which resource is overloaded; it can be either I/O or CPU. Therefore, the deadline of a transaction is divided into two pseudo deadlines, *I/O deadline* and *CPU deadline*, to measure the tardiness of I/O and CPU activities separately. In a transaction, *I/O deadline* and *CPU deadline* are the maximum total time allocated to all I/O operations and all computation activities, respectively. Hence, the sum of the two pseudo deadlines is equal to the deadline of the transaction. The deadlines of transactions are given by applications, and they are fixed at run-time. However, pseudo deadlines are adjusted dynamically at run-time for control-purpose.

Initially, the pseudo I/O and CPU transaction deadlines are determined based on the profiled minimum execution time of I/O operations, $EXEC_{i/o}$, and the computation activities, $EXEC_{cpu}$, in the transaction. $EXEC_{i/o}$ includes the overhead which is proportional to the number of I/O operations, such as looking up the buffer cache, locking index/data pages, but it does not include actual I/O time to access data in the secondary storage since the buffer hit ratio is assumed 100%. $EXEC_{cpu}$ is the minimum execution time of the transaction except the $EXEC_{i/o}$. Given $EXEC_{i/o}$ and $EXEC_{cpu}$, the slack time of a transaction can be obtained:

$$(EXEC_{i/o} + EXEC_{cpu}) \times sf = deadline, \qquad (3)$$

where sf is a slack factor, and it should be greater than one for a transaction to be schedulable in the given system. Hence, the pseudo I/O and CPU deadlines are set initially as follow:

$$deadline_{i/o} = EXEC_{i/o} \times sf, \qquad (4)$$

$$deadline_{cpu} = EXEC_{cpu} \times sf \qquad (5)$$

$$= deadline - deadline_{i/o} \qquad (6)$$

The definition of tardiness in Equation 1 is extended to tardiness in I/O and CPU as follows:

$$tardiness_{i/o} = \frac{response\_time_{i/o}}{deadline_{i/o}} \qquad (7)$$

$$tardiness_{cpu} = \frac{response\_time_{cpu}}{deadline_{cpu}} \qquad (8)$$

However, assigning the same static slack factor for both I/O and CPU deadline can be problematic since the ideal slack times for I/O operations and computation change as the system status changes. For example, when one of the resource is overloaded while the other is not, it would be desirable to allocate more slack time to the overloaded resource since the other resource is under-utilized. To this end, QeDB dynamically adjusts I/O and CPU deadlines at each sampling period by Algorithm 1.

Algorithm 1: Run-time adaptation of deadlines.

Input: average $tardiness_{i/o}$ and $tardiness_{cpu}$
Data: state variables $\tau_{i/o}$ and τ_{cpu}
if $tardiness_{i/o} \geq tardiness_{cpu}$ **then**
  $\tau_{i/o}++$; $\tau_{cpu} = 0$;
  $\delta d = \alpha \times \tau_{i/o}$;
  increase $deadline_{i/o}$ by $\delta d\%$
else
  $\tau_{cpu}++$; $\tau_{i/o} = 0$;
  $\delta d = \alpha \times \tau_{cpu}$;
  decrease $deadline_{i/o}$ by $\delta d\%$
end
$deadline_{cpu} = deadline - deadline_{i/o}$

In Algorithm 1, I/O and CPU deadlines are adjusted by $\delta d\%$ on every sampling period. In a normal state, δd is set to a small number to prevent the high oscillation of deadlines; α is a constant factor and set to 1 in our testbed. However, as a specific resource is being overloaded for consecutive sampling periods, δd increases multiplicatively to speed up the adaptation of pseudo deadlines. Since the sum of the I/O deadline and the CPU deadline is equal to the deadline of the transaction, the multiplicative increase of one pseudo deadline implies the multiplicative decrease of the other pseudo deadline. In the presence of a QoS controller, the overloading of a specific resource happens consecutively when the QoS controller cannot adjust CPU or I/O load any further.

Setting I/O deadlines can serve two purposes: time-cognizant I/O scheduling and I/O workload control. In time-cognizant I/O scheduling, the I/O requests with shorter I/O deadlines are scheduled first to meet the deadlines. In this paper, we use I/O deadlines only for I/O workload control purpose. The controller controls the I/O workload based on $tardiness_{i/o}$. In terms of I/O scheduling, *First-come/First-service* scheduling policy is used for its simplicity. We reserve the study on the impact of the time-cognizant scheduling for future work.

3.2 QoS Management Architecture

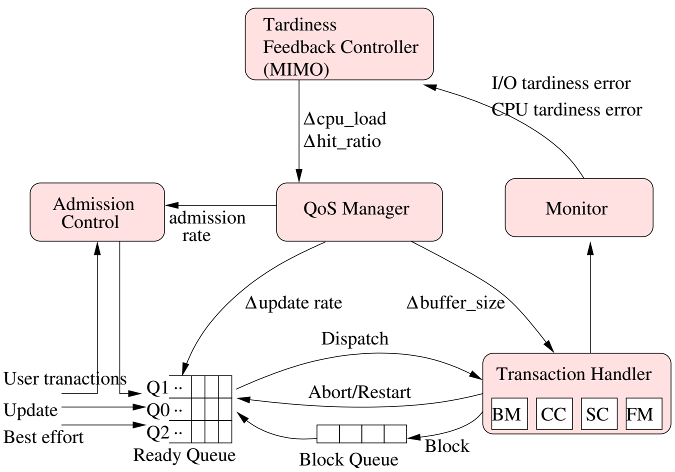


Fig. 3. The QeDB architecture.

Figure 3 shows the QoS management architecture of QeDB. It consists of the MIMO feedback controller, QoS Manager, performance monitor, transaction handler, admission controller, and ready queue.

Admitted transactions are placed in the ready queue. Figure 3 shows three separate queues in the ready queue. Temporal data updates are scheduled in Q0 and receive the highest priority. Q1 handles real-time user transactions. Non-real-time transactions in Q2 have the lowest priority, and they are dispatched only if Q0 and Q1 are empty.

The *transaction handler* manages the execution of the transactions. It consists of a freshness manager (FM), a unit managing the concurrency control (CC), a basic scheduler (SC), and a buffer manager (BM). Transactions in each queue are scheduled in FCFS manner. The FM checks the freshness of a data object before accessing it, using the timestamp and the absolute validity interval of the data. A transaction accessing a data object is blocked if the data object is not fresh. For concurrency control, we apply 2PL (two phase locking) provided by Berkeley DB which is underlying QeDB. Transactions can be blocked, aborted, and restarted due to data conflicts. To reduce the frequency of I/O operations, the BM manages the cache of recently used data. This cache is shared among the processes.

The *monitor* computes the I/O and CPU tardiness, i.e., the difference between the desired I/O (and CPU) response time and the measured I/O (and CPU) response time at each sampling instant. Based on the errors, the *MIMO feedback controller* computes the required buffer hit ratio adjustment (Δhit_ratio) and CPU load adjustment (Δcpu_load).

The *QoS manager* estimates the required buffer size adjustment and update rate adjustment based on Δhit_ratio and Δcpu_load. Update transactions waiting in the ready queues are discarded according to their update rates. The buffer cache size is adapted by the BM in the transaction handler as requested by the QoS manager.

The details of the feedback control procedure follows.

3.2.1 *Feedback control procedure*

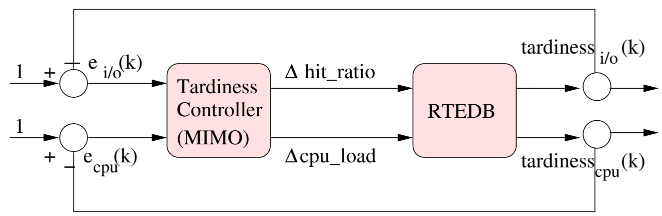


Fig. 4. Tardiness control loop.

The goal of the feedback controller shown in Figure 4 is to support the transaction response time equal to its deadline, which requires the desired tardiness to be 1. The overall feedback control procedure is as follows.

1) At the k^{th} sampling instant, the tardiness errors $e_{i/o}(k)$ and $e_{cpu}(k)$ are computed for I/O tardiness and CPU tardiness, respectively.
2) Based on $e_{i/o}(k)$ and $e_{cpu}(k)$, the MIMO controller computes the control signal Δhit_ratio and Δcpu_load. Unlike a *Single Input/Single Output* (SISO) controller, the MIMO controller computes control signals simultaneously considering both I/O tardiness and CPU tardiness.
3) The QoS manager translates Δhit_ratio to $\Delta buffer\_size$. The QoS manager maintains a linear model that correlates the buffer size to the buffer hit ratio [24]. This linear model is updated at each sampling period since locality of data accesses changes dynamically at run-time. $\Delta buffer\_size$ is achieved by changing the buffer cache size according to this model. Changing the buffer cache size also changes the CPU load as shown in the next section. Therefore, Δcpu_load is adjusted after applying a new buffer size.
4) The Δcpu_load is achieved by adjusting the update rates of the temporal data. For cost-effective temporal data updates, the access update ratio $AUR[i]$ is computed for each temporal data d_i; $AUR[i]$ is defined as $\frac{Access\ Frequency[i]}{Update\ Frequency[i]}$. If $\Delta cpu\_load < 0$, the update rates of a data object, which is accessed infrequently, are adjusted from $p[i]$ to $p[i]_{new}$ [10]. The adjustment changes the CPU load by $(p[i]_{new} - p[i])/p[i]$. This update period adjustment repeats to a subset of temporal data until $\Delta cpu\_load \geq 0$ or no more update rates adaptation is possible.

The details of the feedback control loop design are discussed in the following section.

4 Feedback Control Loop Design

In this section, we take a systematic approach to designing the tardiness controller.

4.1 System Modeling and Verification

The first step in the design of a feedback control loop is the modeling of the controlled systems [23], which in our study are RTEDBs. One approach is to use *first-principles* of the RTEDB. However, the inner workings of complex software systems such as RTEDBs are extremely complicated. Therefore, instead of using the first-principles, we employ *system identification* technique [25]. System identification is an empirical approach that quantifies several system parameters and performance metrics by constructing statistical models from the data.

4.1.1 Selection of system outputs/control inputs

As defined in Section 3, the primary QoS metric in QeDB is transaction tardiness. Hence, we need to choose tuning parameters, or control inputs, to dynamically control transaction tardiness. In selecting appropriate control inputs, two factors should be considered [26]: (1) the parameters must be dynamically adjustable; (2) the parameters must affect the selected performance metrics in a meaningful way. In QeDB, we synthetically divided the tardiness into *CPU tardiness* and *I/O tardiness*. Since QeDB has two QoS metrics, we need at least two control inputs to precisely control them.

Given I/O tardiness as one of the QoS metrics, we can easily choose *buffer hit ratio* as the system parameter to control the I/O tardiness. Intuitively, the higher buffer hit ratio reduces the cost of fetching data objects from secondary storages, virtually decreasing the average I/O response time. In QeDB, the buffer hit ratio is controlled by adjusting the size of the buffer cache.

Regarding CPU tardiness, one available tuning parameter that significantly affects it is the utilization of CPU. High CPU utilization can make the response time of transactions longer due to the high CPU contention among tasks. In RTEDBs, the major factor that decides the CPU utilization is the frequency of temporal data updates since the frequent update of temporal data can significantly increases the CPU overhead. By dropping incoming update requests, we can save the CPU load for handling them at the cost of degrading the freshness of temporal data. However, the lower bound of the update frequency is determined by the application's requirements on data freshness as stated in Section 3.1.

4.1.2 Rationale behind MIMO control

Unlike previous work [14][15], which has single-input, single-output (SISO) control, QeDB in this paper has multiple inputs (hit_ratio and cpu_load) and multiple outputs ($tardiness_{i/o}$ and $tardiness_{cpu}$). We may choose to use two separate SISO models for each pair of control input and system output; one SISO model for relating Δhit_ratio and $tardiness_{i/o}$, and another model for relating Δcpu_load and $tardiness_{cpu}$. However, if an input of a system is highly affected by another input, then a MIMO model should be considered [26] since having two SISO models cannot capture the interactions between the different control inputs and system outputs.

We performed a series of experiments on a testbed to understand the interactions between multiple control inputs and multiple system outputs (the details of the testbed and configuration parameters are discussed in Section 5.) Figure 5 shows the results of varying the cache size while the update rate of the temporal data is fixed. It shows that changing the buffer hit ratio via varying the cache size also changes the CPU load, and they are inversely proportional; increasing the buffer hit ratio decreases the CPU load, and vice versa. This occurs because the I/O operations of QeDB involve not only raw I/O to the secondary storage, but also computation such as searching for data pages in a buffer, locking data/index pages, and finding a least-recently-used page. Therefore, when the buffer hit ratio is low, the CPU load increases proportionally to find LRU pages, and allocate buffer space for new pages from the secondary storage. In the next experiment, the update rate of the temporal data is varied while the buffer size is fixed. Figure 6 shows the results. Update transactions are computation-intensive, and they are expected to only change the CPU load. The result in Figure 6-(b) matches this expectation. While the buffer hit ratio is affected a little by varying the update rates, the effect is negligible. However, Figure 6-(c) shows that changing the CPU load by adjusting the update rates affects both I/O tardiness and CPU tardiness; both the I/O tardiness and the CPU tardiness are proportional to the CPU load. This is because the I/O operations in QeDB involves lots of computation themselves and the increased CPU load makes them preempted more frequently by high priority update transactions. Moreover, increasing the update rates of the temporal data increases the lock conflict rate, making I/O operations wait for the locks. These results show that a MIMO model is required to capture those close interactions of multiple inputs and multiple outputs of QeDB.

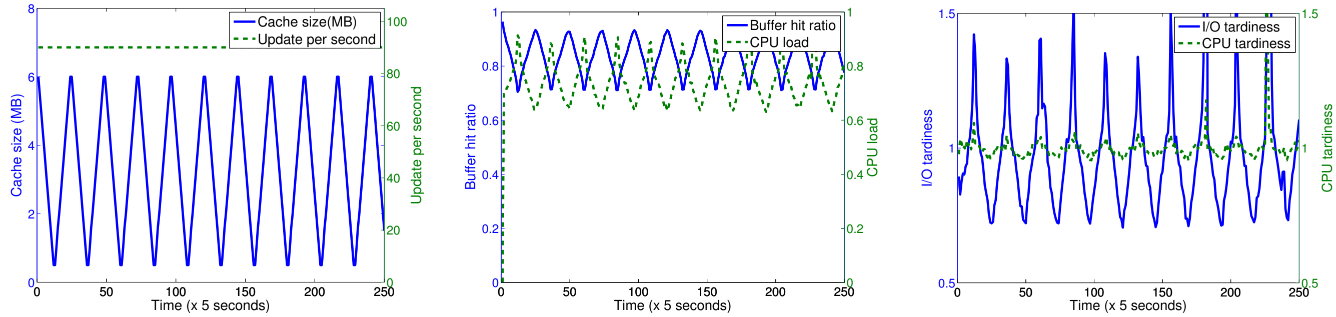
4.1.3 System identification

In the actual system identification [25] of a RTEDB, two inputs are changed simultaneously with relatively prime cycles on the same testbed. The relatively prime cycles are used to fully stimulate the system by applying all different combination of two inputs. The result, which is shown in Figure 7, is used for system modeling.

The form of linear time invariant model for QeDB is shown in Equation 9, with parameters $\mathbf{A}$ and $\mathbf{B}$.

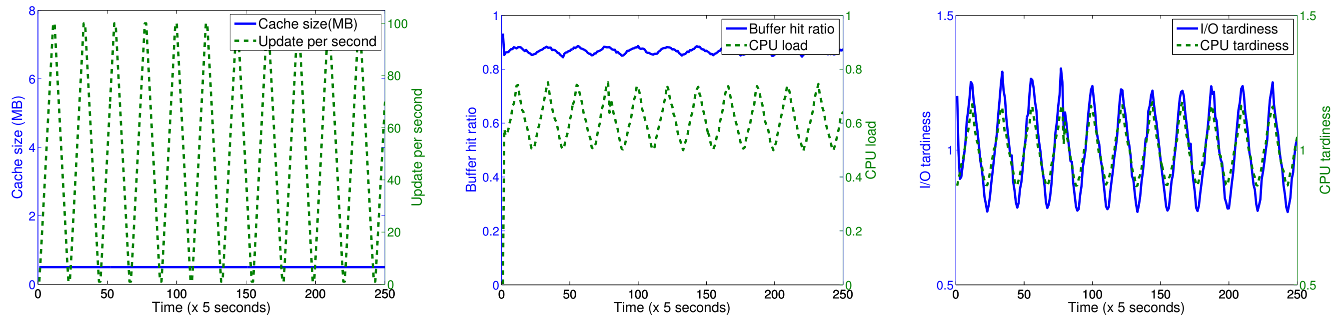
$$\begin{bmatrix} tardiness_{i/o}(k+1) \\ tardiness_{cpu}(k+1) \end{bmatrix} = \mathbf{A} \cdot \begin{bmatrix} tardiness_{i/o}(k) \\ tardiness_{cpu}(k) \end{bmatrix} + \mathbf{B} \cdot \begin{bmatrix} hit\_ratio(k) \\ cpu\_load(k) \end{bmatrix} \quad (9)$$

Because QeDB is modeled as a MIMO system, $\mathbf{A}$ and $\mathbf{B}$ are 2x2 matrices. Note that we model QeDB as a first-order system; the current outputs are determined by their inputs and the outputs of the last sample. In our study, the model has $\mathbf{A} = \begin{bmatrix} 0.275 & -0.266 \\ -0.158 & 0.601 \end{bmatrix}$, and $\mathbf{B} = \begin{bmatrix} -0.255 & 1.980 \\ 0.120 & 0.784 \end{bmatrix}$ as its parameters. All eigenvalues of $\mathbf{A}$ are inside the unit



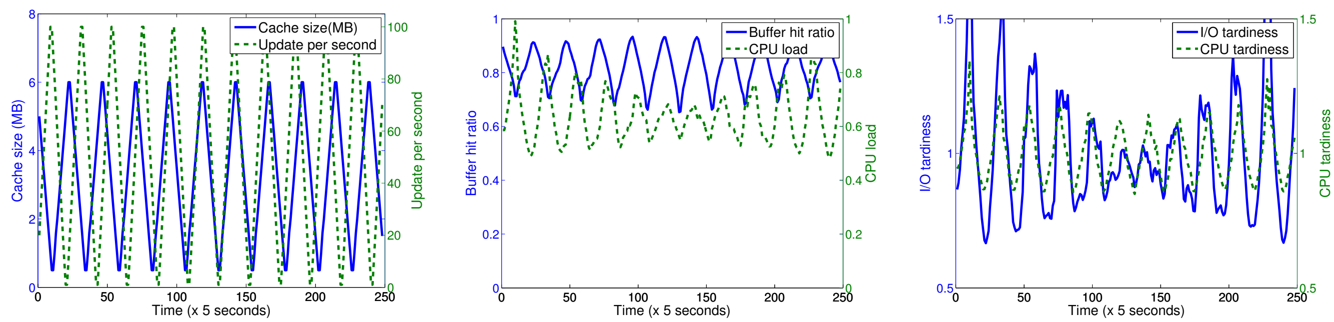
(a) Cache size vs. update rate (b) Buffer hit ratio vs. CPU load (c)I/O and CPU tardiness

Fig. 5. Varying cache size.



(a) Cache size vs. update rate (b) Buffer hit ratio vs. CPU load (c)I/O and CPU tardiness

Fig. 6. Varying update rate.



(a) Cache size vs. update rate (b) Buffer hit ratio vs. CPU load (c)I/O and CPU tardiness

Fig. 7. Varying cache size and update rate simultaneously (System identification).

circle, hence, the system is stable [23]. The accuracy metric R^2 $\left(= 1 - \frac{variance(\text{experimental value - predicted value})}{variance(\text{experimental value})}\right)$ is 0.844 and 0.866 for I/O and CPU tardiness, respectively. This shows that the above model is accurate enough since $R^2 \geq 0.8$ is considered acceptable [23].

One issue in modeling a computing system is its non-linearity and time-variant characteristics. Complex systems such as RTEDBs can show a non-linear response to inputs. For example, the CPU deadline miss ratio develops differently when the CPU is saturated from when it is not saturated. However, the system can be approximated closely with linear time invariant models such as the *ARX* model by choosing an operating region where the system's response is approximately linear [23]. Even when the system's response is highly non-linear, the system can be modeled with linear models by dividing the operating region into several sub-operating regions, which are approximately linear; in this case, adaptive control techniques such as gain scheduling [23] can be used for control. In case of QeDB, the operating region of the controller is set so that the tardiness is bigger than 0.5 and less than 1.5. Since the accuracy of the linear model in the operating region is acceptable, the linear model is sufficient for our purpose.

Another important issue in system identification is choosing a proper sampling interval. In QeDB, the buffer cache affects the choice of sampling interval because the buffer hit ratio changes slowly after adjusting its size. If the sampling interval is too short, controlling the buffer size may not take full effect until the next sampling instant, thus, resulting in phase delays between control inputs and system outputs. Conversely, if the sampling interval is too long, the speed of control will be slow. Our experiments showed that 5 second sampling interval makes a good trade-off between the two conflicting requirements. Hence, in Figures 5, 6, and 7, each point corresponds to a sampling point and takes 5 seconds. Further, it should be noted that in these figures almost no phase delays are observed between the control inputs (cache sizes and update rates) and system outputs (buffer hit ratios and CPU loads). This can be attributed to choosing a proper sampling interval, which is long enough to have effect on the input signals until their next sampling instants.

4.2 Controller Design

For QeDB, we choose to use a proportional integral (PI) control function given by,

$$\mathbf{u}(k) = -\mathbf{K}\begin{bmatrix} \mathbf{e}(k) \\ \mathbf{e}_I(k) \end{bmatrix} = -\begin{bmatrix} \mathbf{K}_P & \mathbf{K}_I \end{bmatrix}\begin{bmatrix} \mathbf{e}(k) \\ \mathbf{e}_I(k) \end{bmatrix} \quad (10)$$

where $\mathbf{K}_P$ and $\mathbf{K}_I$ are proportional and integral control gains, respectively. $\mathbf{K}_P$ and $\mathbf{K}_I$ are 2×2 matrices, hence $\mathbf{K}$ is a 2×4 matrix. At each sampling instant k, the controller computes the control input $\mathbf{u}(k) = \begin{bmatrix} hit\_ratio(k) \\ cpu\_load(k) \end{bmatrix}$ by monitoring the control error $\mathbf{e}(k) = \begin{bmatrix} 1 - tardiness_{io}(k) \\ 1 - tardiness_{cpu}(k) \end{bmatrix}$ and integrated control error $\mathbf{e}_I(k) = \begin{bmatrix} e_{I,1}(k-1) + e_{I,1}(k-1) \\ e_{I,2}(k-1) + e_{I,2}(k-1) \end{bmatrix}$. The control gains, $\mathbf{K_p}$ and $\mathbf{K_I}$, determine the controller's characteristics, which includes the settling time and the overshoot. To obtain proper control gains, we choose to use the *linear quadratic regulator* (LQR) technique, which is accepted as a general technique for MIMO controller design [23]. In the LQR technique, control gains are set to minimize the quadratic cost function,

$$J = \sum_{k=0}^{\infty} [\mathbf{e}(k) \;\; \mathbf{e}_I(k)] \cdot Q \cdot \begin{bmatrix} \mathbf{e}(k) \\ \mathbf{e}_I(k) \end{bmatrix} + \mathbf{u}(k)^T \cdot R \cdot \mathbf{u}(k). \quad (11)$$

The cost function J includes the control errors $\mathbf{e}(k)$, the integrated control errors $\mathbf{e}_I(k)$, and the weighting matrices Q and R. Matrix Q quantifies the cost of control errors and R quantifies the cost of control effort. LQR allows us to better negotiate the trade-off between the speed of response and over-reaction to random fluctuation by selecting appropriate Q and R matrices. The steps in LQR design are 1) selecting the weighting matrices Q and R, 2) computing the control gain $\mathbf{K}$, and 3) evaluating the performance of the new controller by running a computer simulation. These steps repeat by choosing new Q and R if the performance is not suitable.

First, we need to normalize the terms in Equation 11. In QeDB, equal weights on I/O and CPU are imposed by choosing R=diag(1/30, 1/30) since both the buffer hit ratio and the CPU load have a range of [0,1]. In matrix R, component $r_{1,1}$ is the cost associated with I/O control effort and $r_{2,2}$ is the cost for CPU control. For the matrix Q, we focus on the diagonal entries. These entries correspond to the state variables $\mathbf{e}_1(k)$, $\mathbf{e}_2(k)$, $\mathbf{e}_{I_1}(k)$, $\mathbf{e}_{I_2}(k)$, where the subscript 1 refers to the I/O tardiness and the subscript 2 refers to the CPU tardiness. We choose $q_{1,1} = 0.1 = q_{2,2}$ to provide equal costs for the control errors $(\mathbf{e}_1(k), \mathbf{e}_2(k))$. A smaller cost is placed on the integrated control errors $\mathbf{e}_{I,1}(k)$, $\mathbf{e}_{I,2}(k)$, as indicated by the elements $q_{3,3}$ and $q_{4,4}$: Q=diag(0.1, 0.1, 0.005, 0.005). The details of computing $\mathbf{K}_P$ and $\mathbf{K}_I$ using LQR are somewhat involved. Typically, tools such as MATLAB command *dlqr* are employed. For more details on the LQR technique, readers are referred to [23].

5 Implementation

Commonly, embedded databases are used as components of open systems consisting of many other interacting software components and applications, instead of as isolated monolithic databases [16]. To this end, QeDB is intended for use in open systems and built on top of a POSIX-based standard operating system [27], instead of a specialized real-time operating system.

In this section, we describe the system components used in the implementation of QeDB, and discuss some implementation issues not directly related to QoS control.

5.1 Hardware and Software

The hardware platform used in the testbed is the Nokia N810 Internet tablet [28]. The summarized specification of the testbed is given in Table 1. We chose this platform because N810 represents typical modern embedded systems that QeDB is aiming for; it has small main memory space and a large flash memory space, limiting the application of main memory-based RTDB technologies[4]. The flash memory in N810 has 2KB page size and 128KB erase block size. Since flash-based storage is de-facto standard of modern embedded devices as N810, flash-based storage is assumed as secondary storage in QeDB. However, the presented approach of QeDB is not specific to flash-based storage.

The operating system of N810 is *Maemo*, which is a modified version of GNU/Linux slimmed down for mobile devices[5].

TABLE 1
H/W specification of the testbed.

CPU	400MHz TI OMAP 2420
Memory	128 MB RAM
Flash storage	256 MB (on-board), 2GB (SD card)
Network	IEEE 802.11b/g, Bluetooth 2.0

The flash memory of N810 can be accessed through MTD (Memory Technology Device) [29] and JFFS2 (Journaling Flash File Systems, version 2) [30]; database files in QeDB are stored in the flash device via this JFFS2 filesystem. MTD provides a generic interface to access flash devices, which includes routines for read, write, and erase. JFFS2 is a log-structured file system designed for use on flash devices in embedded systems. Rather than using a translation layer on flash devices to emulate a normal hard drive, it places the filesystem directly on the thin MTD layer. JFFS2 organizes a flash device as a log which is a continuous medium, and

4. In N810, the remaining main memory space for user applications is less than 30MB.

5. Maemo is based on GNU/Linux 2.6.21 kernel and compliant with POSIX standards.

data is always written to the end of the log. In a flash device old data cannot be overwritten before erasing, so the modified data must be written out-of-place. Using a background process, JFFS2 collects garbage data.

QeDB is an extension of Berkeley DB, which is a popular open-source embedded database. Berkeley DB provides robust storage features as found in traditional database systems, such as ACID transactions, recovery, locking, multi-threading for concurrency, and slave-master replication for high availability. However, Berkeley DB does not provide the QoS support in terms of transaction tardiness and data freshness, which is the main objective for the design of QeDB.

5.2 Implementation Details and Issues

We discuss several implementation issues and challenges for implementing QeDB.

5.2.1 CPU scheduling

Currently, Linux underlying QeDB supports preemptive real-time scheduling by partially implementing POSIX 1003.b and 1003.c real-time extension features [18][27][6]. Since the POSIX real-time extension does not support optimal real-time scheduling and concurrency control algorithms such as EDF (earliest-deadline-first), they should be implemented in RTEDBs for optimal performance. However, we choose to assign priorities manually to tasks based on their importance, since the experimental results in [31] show that static priority assignment schemes achieve the performance very close to that of EDF when the multi-programming level (MPL) is low; the MPL of real-time tasks in QeDB is typically less than 3.

Four classes of tasks or transactions are defined in QeDB. Different priorities are assigned to them based on their importance as shown in Table 2. First, the control task, which periodically performs monitoring and feedback control of the system, is assigned the highest priority, 15. On every sampling period, the control task calculates and enforces the control inputs by adjusting system parameters, and then sleeps until the next sampling period starts. Update transactions are aperiodic real-time tasks with priority 10 and they are invoked when new updates of temporal data arrives. Update transactions are scheduled by FIFO scheduling policy. We assign priority 5 to user transactions, since delayed sensor data updates can impair the freshness of data. Finally, the priority of best-effort transactions is 0, which is a non-real-time priority.

5.2.2 CPU load measurement

The CPU load is one of the control inputs in QeDB, and the effectiveness of feedback control depends on the preciseness of the CPU load information. In Linux underlying QeDB, several types of CPU information are available for users and applications. First, Linux exports CPU load average information via proc file system (*/proc/loadavg*), and several commands like *top* use this information. However, this information is based on queuing-theoretic estimation by observing the length of *run queue* in the CPU scheduler. Moreover, this does not provide fine-grained information on how much CPU time has been used by a specific set of tasks. Instead of using this CPU load average information, we use the number of clock ticks that have actually been used by the real-time tasks both in user and kernel modes. This information is available via the */proc/stat* interface in Linux. It should be noted that when we measure the CPU load, we only consider the CPU time spent by real-time tasks, since the load incurred by non-real-time tasks does not affect the tardiness of the real-time tasks. The CPU time is assigned to non-real-time tasks only when there is no real-time task. Hence, the CPU load at each sampling period for control purpose is measured as follows:

$$\frac{\text{time spent by real-time tasks in the sampling period}}{\text{sampling period}}. \quad (12)$$

5.2.3 Avoiding double buffering

QeDB uses a file system to store data. When using file systems with a database, the read data is double-buffered in both the file system buffer cache and the DBMS buffer cache. Double buffering not only wastes memory space, but also makes I/O response time unpredictable. DBMS have no control over the filesystem layer buffer cache, since it is controlled by the operating system. QeDB's dynamic buffer adjustment scheme cannot achieve its goal in the presence of double-buffer since changing the buffer size at QeDB only affects the buffer in the DBMS layer. Unfortunately, Berkeley DB for Linux, which is underlying QeDB, does not support direct I/O, or bypassing the file system's buffer cache. QeDB solves this problem by making a separate partition for database files, and disabling the buffer cache of that partition at the file system level. The buffer cache in the file system is disabled by applying modification to the JFFS2 code in the Linux kernel.

6 Evaluation

In this section, we discuss the goal and background of the experiments and present the results.

6.1 Evaluation Testbed

Firefighting has been considered as one of the domains that can best benefit from improvements in timely sensor data gathering, processing and integration. Little timely information can make huge differences in making decisions [20][5][6]. If we can build a system that satisfies the requirements of such a highly stressful domain, we might also be able to apply these results in less extreme environments, such as computing while driving. To this end, a firefighting scenario from [6] is adopted, and simulated on our testbed for more realistic evaluation.

In the scenario, a PDA carried by a firefighter collects sensor data via wireless communication, and a periodic real-time task running on the PDA checks the status of the burning building such as the possibility of collapse, explosion, the existence of safe retreat path, etc. The PDA carried by a firefighter is simulated by a N810 Internet tablet and a stream of sensor data from a building is simulated by a separate 3.0 GHz Linux desktop. The two devices are connected via

6. In POSIX threads, fixed priorities, ranging from 1 to 99, belong to real-time scheduling class and their priority is not dynamically adjusted by the CPU scheduler.

TABLE 2
QeDB tasks.

Task class	Priority	Scheduling policy	periodicity
Control task	15 (real-time)	round robin	periodic
Update transactions	10 (real-time)	FIFO	non-periodic
User transactions	5 (real-time)	FIFO	periodic
Best-effort transactions	0 (non-real-time)	round robin	non-periodic

wireless Ethernet. The desktop simulates 1024 sets of sensors located in the building by continuously sending update reports to the N810. The report period of each set of sensors is uniformly distributed in [1 sec, 10 sec]. In the N810, each update report from the desktop initiates an update transaction to the underlying QeDB. Each set of sensors takes 1KB in storage space, totaling 1MB for temporal database in the N810. The N810 has another 7MB data for non-temporal data such as maps of the building, and engineering data to analyze the status of the building[7].

Every $200ms$, a new QeDB user transaction is instantiated by a local timer in the N810. The user transaction has a similar structure to Program 1 and it simulates the operation of checking the status of the building. The profiled minimum response time, or the execution time, is $31 \pm 0.52ms$ for $EXEC_{I/O}$, and $36 \pm 0.3ms$ for $EXEC_{CPU}$ with 99% confidence. The deadline of the user transaction is set to $110ms$ and the remaining $90ms$ slot is reserved for non-real-time tasks, which are still important for proper operation of the system. For example, our experiment shows that the keypad and GUI components are not working smoothly if the user transaction takes longer than $110ms$. This is similar to having aperiodic servers in real-time scheduling to handle aperiodic tasks [32]. Figure 8 shows the tasks in one period; this period repeats in the experiment.

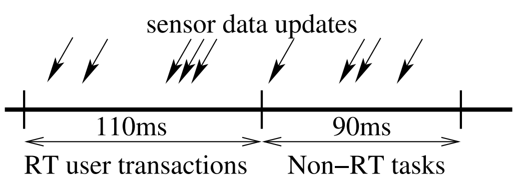


Fig. 8. Tasks in the experiment.

6.2 Performance Evaluation Goals and Baselines

Considering the goal of QeDB, stated in Section 3.1, the two objectives of the performance evaluation are 1) to determine if QeDB can meet the QoS specification given by applications under various conditions and 2) to test the effectiveness of the proposed MIMO control approach.

Considering the first objective, we have studied and evaluated the behavior of the algorithms under various conditions, where a set of parameters have been varied. These parameters are: 1) the ratio of I/O operations to computation in a transaction and 2) access patterns as computation systems may show different behaviors for different workloads.

7. These are raw data sizes. The total storage and memory overhead to keep this raw data in the database system is more than the twice the raw data.

TABLE 3
Tested approaches.

Open	Pure Berkeley DB
CPUonly	RTEDB with SISO control of update rates
QeDB	RTEDB with MIMO control

TABLE 4
QeDB SISO control (CPUonly) parameters.

Control input ($u(k)$)	CPU load
System output ($y(k)$)	average transaction tardiness
Modeling methods	System identification
System model	$y(k+1) = 0.8595y(k) + 0.1449u(k)$
R^2	0.8927
Controller type	PI control
Controller design method	Pole placement ($T_s = 10$ and $M_p = 0.01$)
Controller gain	$K_P = 1.3057$ and $K_I = 0.3319$

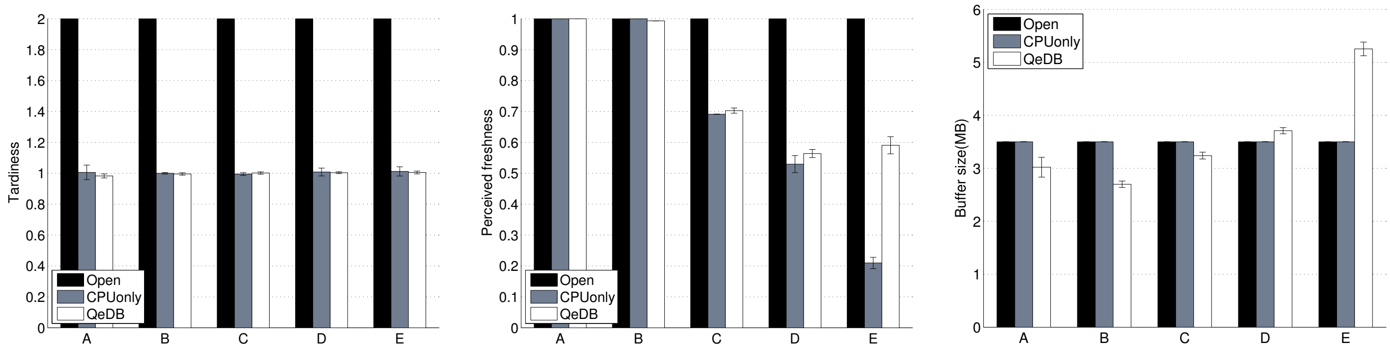
The second objective is investigated by comparing the MIMO-controlled QeDB with different state-of-art approaches with regard to performance adaptation. For performance comparisons, we consider three approaches shown in Table 3. *Open* is the basic Berkeley DB without any special performance control facility. However, the FCFS scheduling with 3 differentiated queues, as in Section 3.2, is still used to process real-time transactions faster. Thus, Open represents a state-of-art database system. In contrast, *CPUonly* represents a RTDB having a QoS management scheme [10], which is not I/O-aware. In CPUonly, as the tardiness of transactions deviates from the desired tardiness, only the CPU workload is adjusted by changing update rates of temporal data. I/O workload is not dynamically controlled. This scheme is originally designed for main-memory RTDBs that have zero or negligible I/O workload. This approach uses a SISO model and controller; the CPU utilization is the control input and the transaction tardiness is the system output. A PI controller is used for CPUonly. Table 4 shows the parameters and settings of CPUonly. Finally, *QeDB* is our approach, which controls both I/O and CPU tardiness using a MIMO controller.

6.3 Average Performance

In this experiment, workloads are varied by applying different user transaction characteristics and data access patterns.

6.3.1 I/O-intensive vs. computation-intensive workloads

The effect of the ratio of I/O operations to computation in workloads is investigated by applying user transactions with different characteristics. Table 5 shows the characteristics of user transactions with different ratios of I/O operations ($EXEC_{I/O}$) to computation ($EXEC_{CPU}$). Among the transaction types, type *A* is the most computation-intensive, and



(a) Tardiness (b) Perceived freshness (c) Buffer size

Fig. 9. Average performance with different I/O-to-computation ratios.

TABLE 5
User transaction properties.

Type	$EXEC_{I/O}$	$EXEC_{CPU}$
A	15ms	53ms
B	27ms	39ms
C	35ms	33ms
D	45ms	23ms
E	55ms	13ms

conversely type E is the most I/O-intensive. The minimum I/O execution time, $EXEC_{I/O}$, is adjusted by changing the number of data object accesses per user transaction. Similarly, the minimum computation time, $EXEC_{CPU}$, is adjusted by changing the loop counts of a dummy computation loop.

Figure 9 shows the average performance of each approach with different I/O-to-computation ratios; the confidence interval is 95%. As shown in Figure 9-(a), both CPUonly and QeDB closely satisfy the tardiness performance goal. In contrast, Open does not achieve the goal in any transaction type. Actually, the tardiness of Open could not be measured in all cases since the system did not respond. In this case the real-time tasks took all the resources, preventing the low-priority tasks from proceeding. The target tardiness is achieved at the loss of data freshness as shown in Figure 9-(b). It quantifies the costs of achieving the target tardiness goals. It is interesting that more degradation in data quality is required as we increase the amount of I/O operations in user transactions. We believe that this result is attributed to the increase of lock conflicts; user transactions have higher chance of conflicts with update transactions as the number of I/O operations increases. The frequent locks and unlocks due to conflicts incur higher load, e.g. context switching cost in QeDB as well as in the operating system layer. Moreover, I/O operations are more costly since they take longer response time to access secondary storages once data objects are not found in the buffer cache. This shows that I/O has high performance impact on the tardiness of transactions, particularly when the ratio of I/O in a transaction is high.

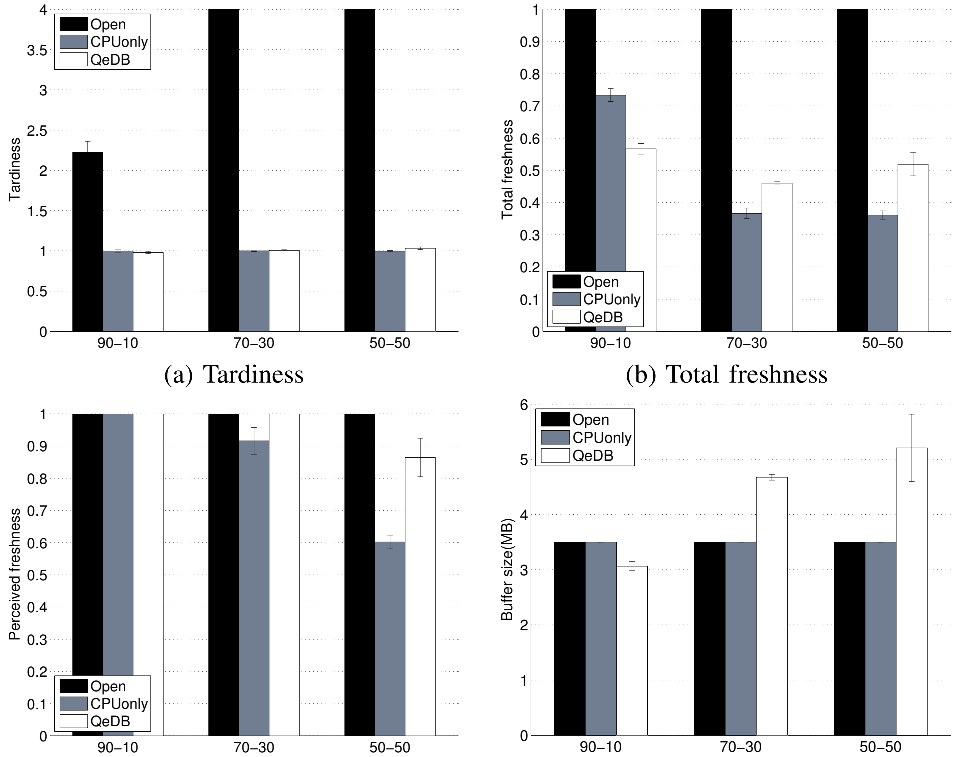
It should be noted that QeDB maintains high data freshness as shown in Figure 9-(b) while the data freshness of CPUonly drops sharply as I/O-to-computation ratio increases. In CPUonly, the data freshness of Type E transactions, which are most I/O-intensive, is 0.20 while QeDB's data freshness is 0.60. This data freshness gap between CPUonly and QeDB derives from the fact that QeDB can effectively control I/O loads by dynamically adjusting the size of the buffer cache. As shown in Figure 9-(c), when transactions are less I/O-intensive, e.g., for types *A, B* and *C*, the buffer cache can be smaller than the default size. Even with the smaller buffer caches, QeDB can still achieve the desired tardiness. In contrast, when transactions are I/O-intensive, e.g., for types *D* and *E*, QeDB maintains the high data freshness by increasing the size of the buffer cache. Type *E* transactions of QeDB consume 50% more main memory than CPUonly's.

6.3.2 Varying access patterns

In this experiment, the effect of data contention is tested using $x-y$ data access scheme. In $x-y$ access scheme, $x\%$ of the data accesses are directed to $y\%$ of the data in the database. For instance, with 90-10 access pattern, 90% of the data accesses are directed to 10% of the data in the database, thus, incurring data contention on 10% of the entire data. We tested the robustness of our approach by applying three different $x-y$ access patterns; 90-10, 70-30, and 50-50.

The average performance for each approach with each data access pattern is shown in Figure 10; the confidence interval is 99%. Figure 10-(a) shows that both CPUonly and QeDB achieve the tardiness goal in all data access patterns. In contrast, Open does not achieve the goal in any data access pattern. The tardiness of Open could not be measured in 70-30 and 50-50 data access patterns because the system did not respond as in the previous I/O-to-computation ratio experiment.

Even though both CPUonly and QeDB achieve the tardiness goal, the trade-offs they make are very different. Figure 10-(b) shows the total freshness, which is the ratio of fresh data to the entire data in the database. CPUonly shows lower data freshness compared to QeDB, and this is even more evident when we consider the perceived freshness of the data as shown in Figure 10-(c). In the 90-10 access pattern, the total size of locality is small, and transactions are CPU-bound since most data access requests can be handled in the buffer with high buffer hit ratio. However, as the data access spreads widely as in 50-50 access pattern, the size of locality becomes larger, and the transactions become I/O-bound since



(a) Tardiness (b) Total freshness

(c) Perceived freshness (d) Buffer size

Fig. 10. Average performance with X-Y access patterns.

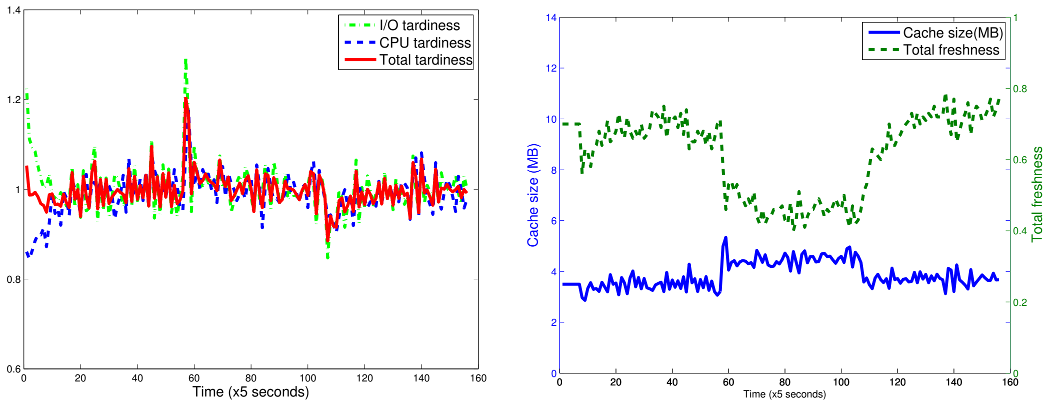
the small buffer of CPUonly incurs low hit ratio. In the CPUonly case, the tardiness is controlled only by adjusting the freshness of the temporal data, regardless of which resource is getting overloaded. Therefore, CPUonly has to lower the freshness of the data excessively, which can be problematic if an application requires high data freshness. For example, the total freshness of CPUonly drops from 0.73 ± 0.02 to 0.37 ± 0.1 when the access pattern changes from 90-10 to 50-50, which is more than 50% degradation of the data freshness. In contrast, QeDB achieves more stable data freshness in all data access patterns. As the size of locality is getting larger, QeDB increases the size of the buffer as in Figure 10-(d), while still maintaining high data freshness. For instance, the buffer size increase about 64% and the total freshness drops 18% when the access pattern changes from 90-10 to 50-50. If we consider the perceived freshness of the data, the difference between CPUonly and QeDB is even higher. The perceived freshness drops only 14% in QeDB while it drops 40% in CPUonly.

6.4 Transient Performance

The average performance is not enough to show the performance of dynamic systems. Transient performance such as settling time should be small enough to satisfy the requirements of applications. In this experiment, the workload increases by introducing a disturbance. For example, consider a situation where peer firefighters opportunistically exchange their temporal data when they are close enough to communicate with each other. This opportunistic data exchange incurs both additional I/O and CPU load to process it. In the experiment, the disturbance is a periodic transaction that lasts for 50 sampling periods. The periodic transaction retrieves 1KB data page with $10ms$ interval.

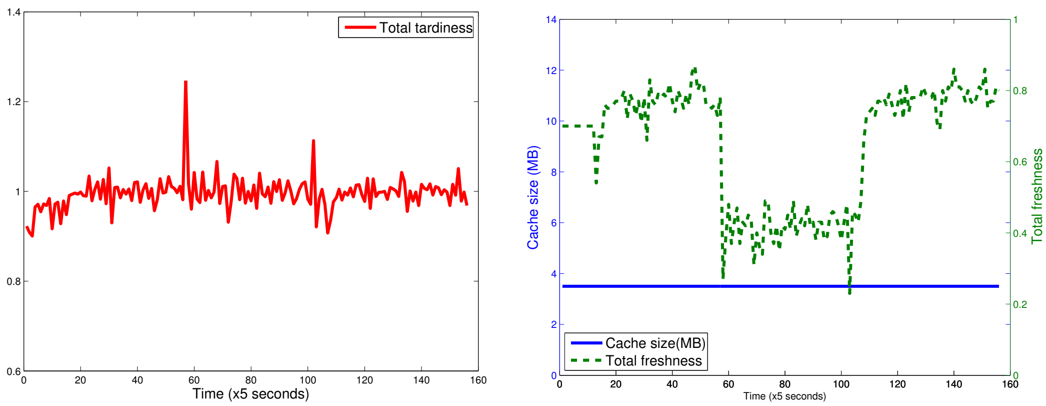
Figure 11-(a) shows the tardiness of real-time transactions. The corresponding buffer hit ratio and data freshness at the same time are shown in Figure 11-(b). The disturbance starts at the 60^{th} sampling period and ends at the 110^{th} sampling period. In Figure 11-(a), we can see that the tardiness increases suddenly at the 60^{th} sampling period. However, the tardiness stabilizes within 3 sampling periods. When the disturbance disappears at the 110^{th} sampling period, it takes 8 sampling periods to stabilize. These long settling times are the result of controller tuning in the controller design phase in Section 4.2. We could reduce the settling times by choosing control parameters for more aggressive control at the controller design time. However, aggressive control results in the higher overshoot and fluctuations in controller inputs (the cache size and update rates). For details on controller tuning, the reader is referred to [33]

Figure 12 shows the transient behavior of CPUonly in the same experiment settings. In coping with the unexpected disturbance, CPUonly exhibits similar transient behavior as QeDB in terms of the settling time and overshoot (see Figure 12-(a)). However, CPUonly makes greater tradeoffs in data freshness to guarantee the desired tardiness as shown in Figure 12-(b). Hence, the data freshness of CPUonly fluctuates highly. The fluctuation magnitudes are 64% and 39%, respectively for CPUonly and QeDB.



(a) Tardiness (b) Buffer size and freshness

Fig. 11. Transient performance of MIMO QeDB.



(a) Tardiness (b) Buffer size and freshness

Fig. 12. Transient performance of SISO QeDB (CPUonly).

7 Related Works

Most RTDB work is based on simulations [34][35][36][13][37][38]. Only a few approaches [16][10][17][39] have actually been implemented and evaluated in real database systems. STRIP (STanford Real-time Information Processor) [16] is one of the first real-time database implementations and it was designed for time-cognizant business applications such as stock trading. The Beehive real-time database supports advanced real-time transaction scheduling based on data deadline, not transaction deadline [17]. Chronos has been primarily designed for high-throughput business applications, and it provides feedback control mechanism to guarantee the target deadline miss ratio of transactions. However, most of these systems are not available publically, or are outdated. QeDB has been developed to address this problem. Moreover, all previous implementations take main memory-based RTDB approaches, limiting their application to a broader range of systems, resource-constrained systems in particular. In contrast, QeDB does not require that all data should reside in main memory.

In the embedded systems domain, several DBMS implementations [40][41] are available. Most of the them are flash memory-based DBMSs, and exploit the peculiar characteristics of flash memory to optimize the resource consumption. Some DBMSs [42][43] target extremely resource-constrained embedded systems such as sensor platforms. However, these DBMSs provide only basic features for accessing data such as indexing. Some features of DBMSs such as concurrency control and guaranteeing logical consistency are usually not supported in these DBMSs. Therefore, their performance optimization is at the flash device level. Moreover, even though they provide efficient mechanisms for accessing data, these approaches are basically best-effort; they do not assure any guarantees on the performance. Unlike these DBMSs, QeDB guarantees the QoS goals set by the applications via feedback control even in the presence of dynamically changing workload.

Feedback control has been actively applied to manage the performance of various systems such as web servers [44], real-time middleware [45], caching services [46], and email servers [47]. In particular, applying control-theoretic approaches to computing systems showed its effectiveness when the operating environments, e.g., workload, are highly dynamic and unpredictable. However, these approaches are not directly applicable to RTDBs, because they do not consider RTDB-specific issues such as data freshness. Moreover, these approaches consider only single resource, e.g., contention in CPU, for QoS management. Unlike these approaches, QeDB manages multiple resources, which have close interaction, via MIMO feedback control.

8 Conclusions and Future Work

In this paper, we propose a novel feedback control architecture to support the desired tardiness of transactions in RTEDBs. In order to provide more efficient and robust control behavior, our approach can control multiple closely interacting resources simultaneously. We showed the feasibility of the proposed feedback control architecture by implementing and evaluating it on a modern embedded system. Our evaluation shows that the simultaneous control of I/O and CPU resource can make a better negotiation between the timeliness of transactions and the freshness of data by providing proper amount of resources in a robust and controlled manner.

In the future, we plan to enhance QeDB in several different directions. First, the feedback control scheme of QeDB will be extended to include other QoS metrics such as power, which is critical in mobile embedded systems. Second, we are interested in coordinating the interaction of multiple control loops in a system. For example, we currently disable *dynamic voltage and frequency scaling* (DVFS) to avoid the interference between the control loops of QeDB and DVFS. Finally, the presence of multiple processors and cores also poses an interesting problem. In multi-processor systems, we need to investigate how the loads of multiple processors affect the timeliness of transactions. This is required to formulate a model that captures their correlation. Currently, our work considers only single processor systems.

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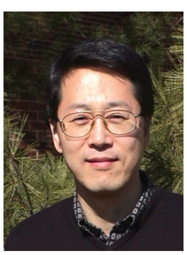
Woochul Kang received his PhD degree from the University of Virginia in 2009. Since Feb. 2000, he is working as an research engineer at Electronics and Telecommunications Research Institute (ETRI) in South Korea. At ETRI, he was the major developer of *Q-Plus* real-time operating system and development tools. His research interests include cyber-physical systems, real-time embedded systems, embedded databases, large-scale distributed systems, feedback control of computing systems, and wireless sensor networks. Currently, he is investigating a distributed middleware architecture that enables efficient and timely access to real-time sensor data in large-scale distributed cyber-physical systems.



Sang H. Son received his Ph.D. in Computer Science at the University of Maryland in 1986. He then joined the University of Virginia as Assistant Professor of Computer Science and was promoted to Associate Professor in 1992, and to full Professor in 1999. He is serving as an Associate Editor of IEEE Transactions on Computers, since Sept. 2007, and served as an AE of the IEEE Transactions on Parallel and Distributed Systems. He is also serving on the editorial boards of the Real-Time Systems Journal, Journal of Information Processing Systems, and Journal of Mobile Communications, Networks, and Computing. He is the chair of the IEEE Technical Committee on Real-Time Systems, and has served as the Program Chair and/or General Chair of several real-time and database conferences, including IEEE Real-Time Systems Symposium, IEEE Conference on Parallel and Distributed Systems, International Workshop on Real-Time Database Systems, IEEE Conference on Electronic Commerce, and International Conference on Networked Sensing Systems. He was President of the Korean Computer Scientists and Engineers Association (KOCSEA), and in 2004, he received the IEEE Outstanding Contribution Award. He is the editor of three books and author or co-author of one book and over 260 refereed papers Son's research focuses on designing and evaluating models and methodologies for the development of robust and responsive computer systems and databases for complex real-time applications. He has been working on supporting multi-dimensional requirements such as real-time, security, and fault-tolerance in distributed data service systems. He also investigated adaptive QoS management in real-time data services using feedback control, real-time data/event services in wireless sensor networks, undersea surveillance using sensor networks, consistency in mobile environments, and applying real-time and database technology in embedded systems.

John A. Stankovic received his Ph.D. from Brown University in 1979 and then served on the faculty of University of Massachusetts at Amherst. He came to UVa as BP America Professor and Chair of the Department of Computer Science in 1997. Professor Stankovic is a Fellow of the IEEE, a Fellow of the ACM, and he served on the Computing Research Association Board of Directors for nine years. He received an IEEE Award for Outstanding Technical Contributions and Leadership in Real-Time Systems, and an Outstanding Scholar Award from the University of Massachusetts. He was Co-Founder and Co-Editor-in-Chief of the International Journal on Real-Time Systems, Editor-in-Chief of IEEE Transactions on Parallel and Distributed Computing, Associate Editor for ACM Transactions on Wireless Sensor Networks, Associate Editor for ACM Transactions on Embedded Systems, and Book Series Editor for Real-Time Systems. Stankovic's primary research interests are in the areas of real-time computing, embedded computing, cyber physical systems, and ad hoc wireless sensor networks. He is investigating various approaches to real-time scheduling, including the development of a theory and practice of feedback control real-time scheduling. He is also involved with building a network virtual machine for wireless sensor networks, and is developing a component-based operating system and associated analysis tools for embedded systems.