An Approach for Real-Time Database Modeling and Performance Management *

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Abstract

It is challenging to manage the performance of real-time databases (RTDBs) that are often used in data-intensive real-time applications such as agile manufacturing and target tracking. Feedback control has recently been considered a promising approach to enabling reliable real-time data service. However, most existing work on feedback control of RTDB performance is not based on a RTDB-specific control model, which is critical for closed-loop system design. To address this problem, we design a novel RTDB model that can capture RTDB dynamics by modeling the relation between the total arrival rate (sum of the transaction arrival rate and restart rate) and utilization via a difference equation. Based on the model, we design and tune a utilization controller to compute the total arrival rate adjustment needed to support the desired average/transient utilization. We also design a QoS management scheme and admission control technique that can judiciously adapt the transaction QoS and arrival rate in a RTDB, if necessary, to support the desired utilization, while enhancing the success ratio. In a simulation study, we show that our approach can support the desired average/transient utilization for a range of transaction arrival rates under severe data contention, while considerably improving the success ratio compared to the tested baselines.

1 Introduction

A number of real-time applications, including agile manufacturing, target tracking, and traffic control, are data-intensive. Real-time databases (RTDBs) are often used in these applications to process transactions within their deadlines using fresh sensor data reflecting the current real world status [5, 25, 26, 31]. Non-real-time databases are inappropriate for these applications as they are unaware of timing and data freshness constraints.

RTDB performance management is challenging due to dynamic data/resource contention. To address the problem, initial work including [4, 5, 10] has applied feedback control theory to RTDB performance management. However, most existing work on feedback control of the RTDB performance (including [4, 5, 10]) is not based on a RTDB-specific system model, which is critical for the closed-loop system design. Instead, their system models are based on the fluid model [9, 24] originally adopted for scheduling real-time tasks involving no data conflicts [16, 18]. Feedback control has been well studied for real-time scheduling and web QoS management in dynamic environments since the early work [2, 15, 17, 16]. However, these approaches are not directly applicable to RTDBs as they do not consider data conflicts specific to databases, which can result in transaction aborts and restarts.

In this paper, we propose a novel approach called **FACT** (Feedback control of Arrivals and Conflicts for Timeliness). FACT directly considers data/resource contention for RTDB modeling. Unlike most existing work such as [4, 5, 10], it requires no knowledge of (estimated) transaction execution times, which are hard to predict due to transaction aborts and restarts [25, 26]. Specifically, we model RTDB dynamics by deriving the relation between the **total arrival rate**, i.e., **transaction arrival rate + restart rate**, and the utilization to represent the possible utilization increase (or decrease) due to varying degrees of data/resource contention¹. A model-based design technique [9, 24] is used to mathematically model the relation between the total arrival rate and utilization. Based on the RTDB model, we design and tune a utilization controller to compute the total arrival rate adjustment necessary to support the desired target utilization at every sampling period. We also develop a transaction QoS adaptation scheme based on the milestone approach [13, 29] and adaptive admission control technique to support the target utilization according to the required total arrival rate adjustment computed in

¹We use the terminology total arrival rate, since the restart of a transaction already in the system could affect the workload in a way similar to a new transaction arrival from the system's perspective.

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the feedback loop, while improving the success ratio under overload.

Without transactions supported by RTDBs, data-intensive real-time applications should manually maintain the temporal and logical consistency of sensor and non-sensor data, possibly producing wrong results based on stale/inconsistent sensor/non-sensor data [25, 26]. Unless transactions are executed serially, no concurrency control protocol can completely eliminate transaction aborts/restarts [7]. Thus, our approach is generally applicable to concurrent real-time transaction processing. To show the applicability of our approach, we consider both lock-based and optimistic concurrency control methods—two major approaches for concurrency control—for performance evaluation. Multi-version concurrency control could further reduce data conflicts in RTDBs. A thorough investigation is reserved for future work.

For performance analysis, we have performed a comprehensive simulation study for various arrival rates under severe data contention. In general, FACT has outperformed the tested baselines often used for RTDB performance comparisons [4, 5, 10, 11]. With no knowledge of the transaction execution time, FACT can closely support the desired average and transient utilization, while considerably enhancing the success ratio compared to the baselines under overload. From this, we observe the applicability of our RTDB model and performance management techniques to reliable real-time data service.

The remainder of this paper is organized as follows. Several performance metrics for real-time data management have been described in Section 2. Our RTDB model and utilization controller are derived in Section 3. A RTDB architecture supporting transaction scheduling, concurrency control, feedback control, QoS management, and admission control is described in Section 4. Performance evaluation is given in Section 5. Related work is discussed in Section 6. Finally, Section 7 concludes the paper and discusses the future work.

2 Deadline Semantics and Performance Metrics

In this paper, we consider *firm deadline* semantics; a real-time transaction is aborted and removed from the system upon its deadline miss to avoid wasting resources to execute tardy transactions. We assume that there are two types of transactions, i.e., sensor transactions and user transactions, similar to [5, 25, 11, 31]. Each sensor transaction is a write-only transaction dedicated to periodically updating one specific sensor data object to maintain its temporal consistency. Thus, the number of sensor transactions is equal to the number of the sensor data objects in the system. User transactions are aperiodic transactions that can read/write

non-sensor data but they can only read sensor data.

We measure the RTDB performance via the *success ratio*, *CPU utilization*, and *QoS* (Quality of Service) received by timely transactions that commit before their deadlines. The success ratio (SR) is defined as follows:

$$SR = 100 \times \frac{N_{timely}}{N_{submitted}}(\%) \quad (1)$$

where N_{timely} is the number of transactions committed before their deadlines and $N_{submitted}$ is the total number of transactions submitted to the RTDB. Thus, the SR indicates what fraction of the submitted transaction can finish within their deadlines. Note that the SR cannot be used as a set-point for feedback control, since $N_{submitted}$ can continuously increase as the workload increases. Hence, it is impossible to support a fixed target success ratio for dynamic workloads. Instead, in this paper, we specify the target utilization for feedback control in a RTDB. As long as we fully utilize the CPU without saturating it, we can maximize the success ratio². It is also known that the relationship between the load applied to the system and utilization can be modeled in a piecewise linear manner [18, 9] as long as the utilization is not saturated at 100%. We further reduce the complexity of RTDB modeling by requiring no *a priori* knowledge of estimated transaction execution times.

In addition to the average utilization, we measure the transient utilization in terms of overshoot and settling time [24, 9]. This is important because, for example, a RTDB can be overloaded due to substantial transient data conflicts and resulting transaction aborts and restarts in a short time interval. In this paper, we apply feedback control to control both the average and transient utilization. We set the sampling period for feedback control $SP = 1s$ as specified in Table 1. We set a range of the target utilization U_t [90%, 95%] to process as many transactions as possible within their deadlines, while avoiding overshoots under overload. Specifically, FACT initializes $U_t = 90\%$. It increments U_t if $SR \geq 99\%$ in a sampling period, which indicates the system is currently underutilized. It resets U_t to 90% as soon as $SR < 99\%$. (A more sophisticated approach for U_t adaptation is reserved for future work.) It is known that the system performance can be improved by adjusting the set-point according to the current workload [9].

To achieve a high success ratio, the target utilization U_t can be dynamically increased up to 95% in our approach. Thus, it is critical to minimize an overshoot, if any, to avoid possible controller saturation at 100% utilization. For example, a 5% overshoot saturates the controller when $U_t = 95\%$. A low U_t , e.g., 80%, can be more resilient to high overshoots. However, it may considerably reduce the

²In this paper, we consider a main memory database model, in which the CPU is considered the main system resource, similar to [28, 6, 31, 5, 10].

Table 1. Desired Feedback Control Performance

Notation	Description	Desired Value
SP	Sampling Period	1s
U_t	Target Utilization	[90%, 95%]
M_p	Overshoot	1%
K_s	Settling Time	250s

success ratio. For these reasons, we require an overshoot $M_p \leq 1\%$ in this paper. Since $M_p \leq 1\%$, the relatively long settling time K_s , which has trade-off relations with M_p , does not significantly affect the RTDB performance.

Imprecise approaches have successfully been applied to real-time transaction processing. Examples include [29, 4, 5, 21]. Our QoS adaptation approach is similar to APPROXIMATE [29], which can monotonically increase the accuracy of the answer to a real-time query by executing it longer, while returning an approximate result, if necessary, to meet the deadline. Specifically, we assume that a transaction T_i consists of one mandatory part T_i^m and p (≥ 1) optional parts $T_{i,1}^o, \dots, T_{i,p}^o$. T_i^m has to be always executed to support the required minimum QoS level for transaction T_i , while $T_{i,j}^o$ ($1 \leq j \leq p$) only refines the results and can be skipped, if necessary, to improve the success ratio under overload. Therefore, the QoS level of transaction T_i is:

$$Q(T_i) = \frac{1 + N_{i,Eopt}}{1 + N_{i,opt}} \quad (2)$$

where $N_{i,Eopt}$ and $N_{i,opt}$ represent the number of the *executed* optional parts and the total number of the optional parts in T_i . Thus, $0 \leq Q(T_i) \leq 1$. From this, we define the average QoS in a RTDB:

$$QoS = 100 \times \sum_{T_i \in S_{timely}} \frac{Q(T_i)}{N_{timely}} (\%) \quad (3)$$

where S_{timely} is the set of transactions completed within their deadlines and N_{timely} is the cardinality of S_{timely} .

3 RTDB Modeling and Controller Design

In this section, we propose a RTDB model that considers not only transaction arrivals but also restarts. Section 3.1 describes our open-loop RTDB model in terms of total arrival rate and utilization. In Section 3.2, the RTDB model parameters are derived via system identification. Based on the results, the closed-loop transfer function is derived in Section 3.3. Given the closed-loop transfer function, the controller is tuned by the Root Locus method [24] to support the overshoot and settling time chosen in Table 1. Due

to this systematic modeling and tuning procedure, the desired overshoot and settling time can be satisfied (as discussed in Section 5).

3.1 RTDB Model

It is known that the transaction arrival rate is useful to model a RTDB in which transaction execution times are usually not known *a priori* [22]. We have performed a simulation in which the utilization is measured for the increasing transaction arrival rate. To model RTDB dynamics under overload, no feedback control, admission control, or QoS degradation is applied in these experiments. (A detailed description of our simulation settings is given in Section 5.) In Figure 1, the utilization increases and saturates at 100% as the average arrival rate, indicated by *tps* (*transactions per second*), increases. Notably, the success ratio sharply decreases as the arrival rate further increases after the utilization is saturated due to the severe data/resource contention. Thus, it is necessary to avoid the saturation by controlling the arrival rate.

Figure 1. Average Utilization

Figure 2. User Transaction Restart Rate

High data contention can also increase the utilization due to many transaction aborts and restarts, causing database thrashing in an extreme case [20]. Figure 2 shows the restart

Figure 3. Transient Utilization

rate when the average arrival rate is only 30 tps at which the average utilization is below 80% as shown in Figure 1. In Figure 2, the transaction restart rate is often greater than 20 tps and it even reaches 110 tps. From these experiments, we observe that it is critical to consider not only the *arrival rate* λ but also the *restart rate* λ_r . From Figures 1 and 2, we observe that the maximum transient *total arrival rate* $\lambda' = \lambda + \lambda_r = 30 \text{ tps} + 110 \text{ tps} = 140 \text{ tps}$ when λ is only 30 tps. For the same arrival rate 30 tps, the transient utilization is shown in Figure 3. Although the *average* utilization is only 79.02% as shown in Figure 1, the *transient* utilization widely fluctuates saturating at 100% several times as shown in the figure. Thus, a system model only based on the arrival rate such as the one used in [22] can involve large errors. If a RTDB model does not consider the restart rate in addition to the arrival rate, too many transactions can run concurrently, further increasing data/resource contention. Consequently, the success ratio could be decreased drastically.

To address the problem, we propose a new utilization control model for RTDBs by considering both the arrival rate and the restart rate. Specifically, we construct a RTDB model based on the ARX (Auto Regressive eXternal) model [24, 9] that are widely used to model computational system dynamics [9, 15, 3, 19, 23]. The ARX model expresses the next output based on the n previous system inputs and outputs where $n(\geq 1)$ determines the system order. Specifically, we model the relationship between the total arrival rate $\lambda'(k)$ and utilization $u(k)$ at the k^{th} sampling period over the sampling history in the discrete time domain as follows:

$$u(k) = \sum_{i=1}^n \{a_i u(k-i) + b_i \lambda'(k-i)\} \quad (4)$$

where the total arrival rate $\lambda'(k-i) = \lambda(k-i) + \lambda_r(k-i)$, i.e., the sum of the transaction arrival rate and restart rate measured at the $(k-i)^{th}$ sampling period. By considering both the new transaction arrivals and the aborts/restarts of the transactions already in the system, our model can effectively express RTDB dynamics. The model parameters, i.e., a_i 's and b_i 's in Eq 4, can be derived via system identifica-

tion [9, 24] discussed next.

3.2 System Identification

Figure 4. System Identification Steps

In this subsection, the procedure of the system identification based on the RTDB model described in the previous subsection is presented. Figure 4 illustrates a well-established five step procedure for black-box modeling [24, 9]. We follow this procedure to identify the system dynamics by finding and verifying the model parameters in Eq 4 in a systematic manner as follows.

Figure 5. Model Verification

Step 1: Specify the model scope. To see the effect of the arrival/restart rate on the utilization, we have observed how the RTDB utilization changes for the increasing arrival rate as discussed in the previous subsection. From Figure 1, we observe that the utilization increases in a nearly linear fashion between $\lambda = 10 \text{ tps}$ and $\lambda = 40 \text{ tps}$. Once $\lambda > 40 \text{ tps}$, the utilization gets saturated as shown in the figure. Hence, we select the arrival rate range [10 tps, 40 tps] as our model scope, since standard linear control theoretic techniques can be applied to identify the system model within this range of the arrival rates. Specifically, we identify the relationship between the total arrival rate and utilization within this scope. (A more detailed discussion is given in the Steps 2 and 3.) In addition, we have to determine the order of the ARX model (Eq 4). A higher order model can generally

(but not necessarily) improve the accuracy of the model for more complexity [9]. Thus, we have constructed four different models: 1st, ..., 4th order models. (A more detailed discussion is given in the Step 4.)

Step 2: Design experiments. In this step, we collect system dynamics data to estimate model parameters, i.e., a_i 's and b_i 's in Eq 4. Although the model scope is specified in the Step 1, the variability of the transient utilization is a remaining issue to deal with. In Figure 3, for example, the transient utilization considerably fluctuates for a moderate workload where $\lambda = 30$ tps that results in the approximately 79% average utilization (Figure 1). To smooth the variability of the utilization due to stochastic workloads and dynamic data contention, representative workloads and a large number of system dynamics data— λ' and u in our approach—should be used and collected [24, 9]. To address this issue, we use well-accepted real-time transaction processing workloads, similar to [31, 5, 10]. For unbiased parameter estimation, we uniformly change the arrival rate λ within the range [10tps, 40tps] specified in the Step 1 at every 10s in which approximately 100 (1000) transactions newly arrive when $\lambda = 10$ (100) tps. To collect a large number of performance data, we run a simulation for 60 minutes and obtain λ' and u at every 10s.

Step 3: Estimate the model parameters. We apply the least square regression method [24, 9] to estimate model parameters in Eq 4 to minimize the sum of the squared prediction errors. Specifically, the prediction error in our model $e(k) = u(k) - u'(k)$, where $u(k)$ is the utilization measured at the k^{th} prediction period and $u'(k)$ is the utilization predicted by Eq 4 using the estimated model parameters available at the k^{th} period. The least square regression method iteratively estimates the model parameters at each sampling instant to minimize the sum of the squared estimation errors $\sum_{k=1}^m e(k)^2$ where m is the number of the sample instances. We apply the least square regression method to the four different orders of models to compare their accuracy as follows.

Step 4: Evaluate the model. Once the model parameters are estimated from the Step 3, we need to evaluate whether or not system dynamics are well captured by the model. In Figure 5, we plot the squared error (SE) $e(k)^2$ at every 10s to evaluate the accuracy of the 2nd order model. As shown in the figure, the SE is below 0.02 for most of the time. The corresponding root mean square error (RMSE), which is a common correctness metric for system identification [24, 9], is: $RMSE = \sqrt{\sum_{i=1}^{360} e(i)^2 / 360} = 0.0852$, while $RMSE' = \sqrt{\sum_{i=181}^{360} e(i)^2 / 180} = 0.0685$ without the initial spikes of errors. The 1st order model has shown the highest error, while the 3rd and 4th order models have not improved the accuracy considerably. Thus, we have selected the second order model due to its high accuracy for

less complexity compared to the higher order models. This selection complies with the rule of thumb recommending to select the lowest order model with good accuracy [9].

Step 5: Determine if the model is acceptable. This step determines whether or not the chosen model is acceptable. In this paper, we accept the second order model, since it effectively captures system dynamics as shown in Figure 5. Further, our feedback control scheme based on the second order model has achieved good performance. (The detailed performance results will be discussed in Section 5.) The final second order model derived via this five step procedure describes the relationship between λ' and u in the discrete time domain as follows:

$$u(k) = 0.5092u(k-1) + 0.2187u(k-2) + 0.01175\lambda'(k-1) - 0.00438\lambda'(k-2) \quad (5)$$

3.3 Utilization Controller Design

As shown in Figure 6, the utilization controller computes the control signal $\Delta\lambda'$ based on the error, which is the difference between the target utilization U_t and the utilization measured at a sampling instant. Specifically, $\Delta\lambda'$ is the control signal by which the RTDB needs to decrease (or increase) λ' to achieve the desired utilization U_t when overloaded (or underutilized).

As the first step to designing the utilization controller, the transfer function of the RTDB is derived by taking the z -transform [24, 9] of Eq 5 to describe the relationship between λ' and u such that the transfer function can be expressed in an algebraic manner:

$$U(z) = 0.5092z^{-1}U(z) + 0.2187z^{-2}U(z) + 0.01175z^{-1}\Lambda'(z) - 0.00438z^{-2}\Lambda'(z) \quad (6)$$

where $U(z)$ is the z -transform of $u(k)$ and $\Lambda'(z)$ is the z -transform of $\lambda'(k)$. After some algebraic manipulation, we get the following transfer function:

$$G(z) = \frac{U(z)}{\Lambda'(z)} = \frac{0.01175z - 0.00438}{z^2 - 0.5092z - 0.2187} \quad (7)$$

Given the transfer function in Eq 7, we can design the utilization controller using a standard controller such as a PID (Proportional-Integral-Derivative) controller [24, 9]. In this paper, we use a PI controller for the following reasons. A P controller cannot remove the steady state error [24, 9]. We have verified this phenomenon via simulation in which the tested P controllers failed to support the target utilization. An integral controller can be combined with a P controller to eliminate the non-zero steady-state error [24, 9]. A derivative controller could decrease the settling time by adjusting the control input based on changes in control errors. However, a weakness of derivative control is the sensitivity

Figure 6. Utilization Control Loop

to noise [24, 9]. Since RTDB workloads are stochastic involving transaction aborts and restarts, we do not use a D controller in this paper.

The PI control law for our utilization controller is:

$$\Delta\lambda'(k) = K_P[e(k) + K_I \sum_{i=1}^k e(k)] \quad (8)$$

where the error $e(k) = U_t - u(k)$ at the k^{th} sampling period. As shown in Figure 6, $e(k)$ is the input to the utilization controller that computes the control signal $\Delta\lambda'$, i.e., the required λ' adjustment at the k^{th} sampling period, based on $e(k)$. K_P and K_I are the proportional and integral control gains. The gains should be chosen carefully to support the desired average and transient performance specified in Table 1. Eq 8 can be rewritten in a more efficient form:

$$\Delta\lambda'(k) = \Delta\lambda'(k-1) + K_P[(K_I + 1)e(k) - e(k-1)] \quad (9)$$

The transfer function of a PI controller can be obtained by taking the z -transform of Eq 9 to describe the relation between the controller input $e(k)$ and the controller output $\Delta\lambda'(k)$:

$$C(z) = \frac{\alpha(z - \beta)}{z - 1} \quad (10)$$

where $\alpha = K_P(K_I + 1)$ and $\beta = 1/(K_I + 1)$.

To support the desired control performance summarized in Table 1 by tuning K_P and K_I , we need to find the closed-loop transfer function. In control theory, the closed loop transfer function can be derived using the transfer functions of the controller and the controlled system such as the RTDB [24, 9]. Given the RTDB transfer function $G(z)$ (Eq 7) and PI controller transfer function $C(z)$ (Eq 10), the closed loop transfer function $F_R(z)$ is [24, 9]:

$$F_R(z) = \frac{C(z)G(z)}{1 + C(z)G(z)} \quad (11)$$

Given this closed loop transfer function, we use the Root Locus method [9, 24] to graphically tune the PI controller in Matlab. In this way, we can locate the closed-loop poles to support the desired performance specified in Table 1. The exact location of the closed-loop poles are -0.289 and $0.876 \pm 0.053i$. (The corresponding $K_P = 0.8$ and $K_I = 4$.) Since the poles are inside the unit circle, the closed-loop system is stable.

4 Success Ratio Management via Utilization Control

This section describes the way the key system components such as the transaction scheduler (TS), concurrency controller (CC), admission controller, and QoS manager interact based on the control signal computed at every sampling period.

Figure 7. Real-Time Database Architecture

Figure 7 illustrates the RTDB architecture designed to support a high success ratio. There are two types of transactions. Sensor transactions periodically update the sensor data in the RTDB to reflect the current real-world status. User transactions arrive aperiodically. They can read sensor data and read/write non-sensor data as discussed before. The Transaction Handler schedules transactions in an EDF (Earliest Deadline First) [14] fashion. It supports both pessimistic and optimistic concurrency protocols: two phase locking high priority (2PL-HP) [1] and Wait-50 [8]. In 2PL-HP, which is pessimistic, all data conflicts are immediately resolved by aborting lower priority transactions. Hence, 2PL-HP is free of priority inversion. Wait-50 is a well known optimistic concurrency control protocol, in which a validating transaction can commit when it has a higher priority than more than half of the transactions conflicting with itself. We consider both 2PL-HP and Wait-50, since the performance of real-time concurrency control mechanisms varies depending on several factors such as the degree of data/resource contention or deadline semantics [12]. The Monitor measures the system status such as the utilization $u(k)$ and success ratio $SR(k)$ at the k^{th} sampling period. It can dynamically adjust U_t based on the success ratio as discussed in Section 2. Based on the difference between the target utilization and monitored utilization, the Utilization Controller computes $\Delta\lambda'(k)$ that is the λ' adjustment required to support U_t .

As described in Figure 8, the QoS Manager and Admission Controller adapt the workload according to the control signal. Note that QoS degradation is applied before admission control to improve the success ratio. When the system

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1. At the k^{th} sampling period, the Monitor receives $u(k)$ and computes the utilization error $e(k) = U_t - u(k)$.
 2. Based on $e(k)$, the Utilization Controller computes the control signal $\Delta\lambda'(k)$. Under overload, $\Delta\lambda'(k) < 0$ requiring the RTDB to reduce data/resource contention. If $\Delta\lambda'(k) \geq 0$, skip the Step 3.
 3. When $\Delta\lambda'(k) < 0$, the QoS Manager degrades the QoS of the transactions in the system to support the desired utilization by applying the milestone approach [13], similar to [29]. After degrading transaction T_i , adjust $\Delta\lambda'(k) = \Delta\lambda'(k) + 1 - Q(T_i)$ where $Q(T_i)$ is the QoS level of T_i computed using Eq 2. Perform all possible QoS degradation until $\Delta\lambda'(k) \geq 0$ or no transaction can be degraded anymore.
 4. Apply admission control to the transactions arriving during the $(k + 1)^{th}$ sampling period. In this period, admit no more than $\lambda_a = \lambda(k) + \Delta\lambda'(k)$ incoming transactions.
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Figure 8. FACT Procedure

is overloaded due to data/resource contention, $\Delta\lambda'(k) < 0$. In this case, a subset of transactions in the system can be degraded. When transaction T_i is degraded, its QoS level $Q(T_i)$ (defined in Eq 2) monotonically decreases as more optional parts are skipped, similar to [13, 29]. Since $1 - Q(T_i)$ represents the fraction of the original transaction that is not executed due to the QoS degradation, the QoS degradation is conceptually equivalent to decreasing the arrival rate by $1 - Q(T_i)$. Data/resource contention can be decreased in this way, because a degraded transaction will access a reduced number of data doing less arithmetic/logical computation. Hence, we increase $\Delta\lambda'(k)$ by $1 - Q(T_i)$ after degrading T_i to $Q(T_i)$. We repeat the QoS adaptation until $\Delta\lambda'(k) \geq 0$ or no transaction can be degraded anymore.

In the next sampling period, i.e., $(k + 1)^{th}$ sampling period, FACT admits no more than λ_a transactions where $\lambda_a = \lambda(k) + \Delta\lambda'(k)$. Thus, FACT admits more transactions in the next period when $\Delta\lambda'(k) > 0$. In contrast, FACT admits a smaller number of transactions in the next period if $\Delta\lambda'(k) < 0$ to avoid overloads by reducing the arrival rate. Especially in this case, FACT admits incoming transaction T_i with the degraded QoS $Q(T_i)$ and consider that only $Q(T_i)$ (< 1) transaction is admitted. In this way, it can admit more transactions to enhance the success ratio under overload.

5 Performance Evaluation

For performance evaluation, we have built a RTDB simulator to model the RTDB architecture depicted in Figure 7. We have performed all the experiments described in this section for both 2PL-HP [1] and Wait-50 [8]. For Wait-50, we have performed separate RTDB modeling, system identification, and controller tuning described in this paper. However, we only present the results under 2PL-HP due to space limitations. Generally, FACT has shown a slightly better performance with Wait-50. We run one simulation for 20 simulated minutes. Each performance data presented here is the average of 10 simulation runs. Since the 90% confidence intervals are below 3%, we do not plot them for the clarity of presentation. Further, we ignore the overhead of feedback control, because it is known to consume less than 1% CPU utilization [19].

A number of RTDB applications, e.g., agile manufacturing, traffic control, and target tracking, monitor the real world status via periodic sensor readings, while processing user transactions in a timely fashion using sensor and non-sensor data. Our workloads are similar to the workloads commonly found in the RTDB literature including [31, 5, 10]. The workloads of [31] are derived from air traffic control. The workloads of [10] are modeled after stock trading, while the workloads of [5] are similar to [31, 10] except data imprecision considered in their work. A more detailed discussion follows.

Data and Sensor Transactions. There are 1000 sensor data and 1000 non-sensor data in the (simulated) RTDB. The sensor data objects are periodically updated by 1000 independent sensor transactions. Sensor transaction ST_i 's period P_i is uniformly distributed in a range (100ms, 50s). The relative deadline of ST_i is equal to its period P_i . ST_i 's execution time is uniformly distributed in a range (3ms, 6ms). The total utilization required by the sensor transactions is approximately 50%. All periodic sensor transactions meet their deadlines to support the basic data temporal consistency requirement specified by the absolute validity intervals [25].

User Transactions. The execution time ET_j of user transaction T_j is uniformly distributed in a range (5ms, 20ms) and T_j 's deadline $D_j = T_j$'s arrival time + slack factor (SF) $\times ET_j$ where the SF is uniformly distributed in a range (10, 20). The number of T_j 's data accesses is proportional to ET_j . If ET_j is 5ms, for example, T_j performs 5 read/write operations (and computations). An operation in T_j accesses a sensor data with probability 0.4. Thus, user transaction T_j reads 2 sensor data items and writes 3 non-sensor data items when $ET_j = 5ms$. For T_j , we set the conditional probability $P(\text{write}|\text{non-sensor data access}) = 1$ to create data conflicts, which can stress FACT and the tested baselines. Because a sensor data item i is updated by a dedicated sen-

sensor transaction ST_i and user transactions can only read sensor data, we do not need full concurrency control for sensor data. Instead, we use short latches to prevent user transactions from reading sensor data, while they are updated, similar to [31]. Hence, neither sensor nor user transactions are aborted/restarted due to sensor data accesses. To model high data contention, we follow the 90-10 access pattern, in which 90% of RTDB accesses are directed to the 10% of the data in the RTDB. Note that FACT and the tested baselines are unaware of ET_j and the data access pattern. A transaction consists of a mandatory part and optional parts, similar to [29]. When T_j is fully degraded, we assume that ET_j and $Q(T_j)$ are reduced by 30% to 60% in a uniform random manner to consider the fact that different transactions may allow different degrees of QoS degradation. User transactions follow the Poisson arrival pattern. The average arrival rate λ is varied from 10 tps to 100 tps. The load applied to the RTDB is approximately 60% when $\lambda = 10$ tps and 170% when $\lambda = 100$ tps.

Baselines. Given the sensor and user transaction workload settings, we use the following baseline approaches that have been widely used for performance comparisons in RTDBs [5, 10, 11]. (i) *Admit-All* admits all incoming transactions regardless of the current system status. It does not degrade the QoS either. (ii) *Ad-Hoc* rejects all incoming user transactions when the utilization is higher than the target utilization U_t , similar to [11, 20]. Unlike FACT, U_t is fixed at 95% for Ad-Hoc to admit as many transactions as possible to enhance the success ratio. Further, it does not degrade the QoS. We consider this baseline, since admission control is known to be very effective to deal with overloads in database systems [5, 11, 10, 30]. In addition, we consider (iii) *FACT without QoS*, which applies the control theoretic approach and admission control method described in this paper without adapting QoS. Note that existing work on feedback control of RTDB performance including [4, 5, 10] assume knowledge of estimated transaction execution times, whereas FACT does not. Thus, they are not directly comparable to FACT. FACT could also perform better when estimated execution times are known in certain cases. A thorough investigation is reserved for future work.

Performance Results. Figure 9 illustrates the average utilization for the increasing average arrival rate λ . The average utilization of Admit-All gradually increases and saturates when $\lambda \geq 60$ tps, overloading the RTDB. Ad-Hoc supports the desired 95% average utilization for $\lambda \geq 60$ tps, because it drops every incoming transaction whenever the utilization $> 95\%$. However, its success ratio quickly drops as λ increases due to aggressive admission control. (A detailed discussion of the success ratio will follow shortly.) Further, its transient utilization significantly fluctuates, since it does not continuously control the utilization in a feedback loop as FACT does. FACT without QoS closely achieves the de-

Figure 9. Average Utilization

sired 95% utilization when $\lambda \geq 60$ tps. It also supports the desired transient performance specified in Table 1. (The transient performance results of Ad-Hoc, Admit-All, and FACT without QoS are not included due to space limitations.) By applying QoS management and admission control according to the control signal, FACT successfully supports the target utilization $U_t \in [90\%, 95\%]$ for $\lambda \geq 40$ tps. FACT shows flexible utilization management in the specified range of U_t to improve the success ratio by increasing U_t within the bound when the success ratio $\geq 99\%$, while avoiding overshoots and resulting saturations by decreasing U_t under overload as discussed in Section 2. From the figure, observe that FACT reduces its utilization set-point U_t as λ exceeds 60 tps. As a result, the average utilization of FACT becomes 91.35% when $\lambda = 100$ tps.

Figure 10. Average Success Ratio

In Figure 10, FACT's success ratio is 100% when $\lambda \leq 50$ tps. Its success ratio is considerably higher than Admit-All and Ad-Hoc when $\lambda \geq 60$ tps. It enhances the success ratio by 20% – 30% compared to Admit-All and Ad-Hoc by dynamically adapting the system behavior via feedback control, QoS degradation, and admission control consider-

ing the current data/resource contention. Ad-Hoc generally shows the lowest success ratio among the tested approaches due to its aggressive admission control. For $\lambda \geq 90$ tps, due to admission control, its success ratio is slightly higher than Admit-All, which is severely overloaded; however, the difference is less than 3%. The success ratio of FACT without QoS is slightly higher than Ad-Hoc, but its transient utilization is stable unlike Admit-All and Ad-Hoc showing a lot of fluctuations. Thus, FACT without QoS could provide more reliable real-time data service than Admit-All and Ad-Hoc.

Figure 11. Average QoS

The average QoS supported by FACT is shown in Figure 11. FACT gracefully degrades the QoS as λ increases. Its QoS is initially 100% and reduces to 54.98% when $\lambda = 100$ tps. Since Admit-All and Ad-Hoc do not support the QoS adaptation, the average QoS is 100% for every arrival rate, causing the poor success ratio especially at high arrival rates as shown in Figure 10.

Figure 12 shows the transient performance of FACT for the relatively high arrival rates that result in more than the 90% average utilization (Figure 9). When $\lambda < 40$ tps, FACT has shown no overshoot of the transient utilization. (We do not plot the transient performance for $\lambda < 40$ tps due to space limitations.) Since Admit-All fails to maintain U_t and the success ratio of Ad-Hoc is generally lower than Admit-All, we only show FACT's transient utilization and QoS. We consider the RTDB is in the steady state when the transient utilization is between [90%, 95%] specified in Table 1. In Figure 12, the utilization is never saturated at 100% after the system becomes stable for all the arrival rates. The settling time K_s is less than the required 250s (Table 1) for all the tested arrival rates. Specifically, $K_s = 14s, 30s, 213s$ and $249s$ for $\lambda = 40$ tps, 60 tps, 80 tps, and 100 tps, respectively. After being stabilized, the transient utilization mainly stays between [89%, 96%], closely satisfying the transient performance requirements. From the figure, we also observe that FACT dynamically degrades the QoS to avoid overload. Especially, this phenomenon be-

Figure 12. Transient Utilization and QoS of FACT

comes more evident as λ increases. Figures 12(a) and 12(b) show some QoS fluctuations. This is because FACT dynamically adapts U_t to increase the success ratio whenever there is a chance. As a result, the fraction of transactions (incoming or already in the system) to be degraded may vary. In addition, we measure the QoS for timely transactions that commit within their deadlines. Thus, transactions degraded at a certain time can commit at different times, introducing variations in the measured QoS. (More advanced QoS management is reserved for future work to reduce QoS variations.) In contrast, the QoS is relatively stable for $\lambda = 80$ tps and $\lambda = 100$ tps as shown in Figure 12(c) and Figure 12(d). This is because the RTDB does not increase U_t and degrades most transactions to avoid overload. From

these results, we can conclude that FACT can support both the required average and transient utilization, while substantially improving the success ratio, via feedback control, QoS management, admission control, with no knowledge of the transaction execution time.

6 Related Work

Feedback control has been applied to real-time task scheduling to manage the utilization and deadline miss ratio given unpredictable loads [16, 18]. Most existing RTDB work on feedback control including [4, 5, 10] has adopted control theoretic models similar to [16, 18] to manage the transaction timeliness and data freshness/imprecision. However, these work do not consider database-specific transaction aborts/restarts for RTDB modeling. They also require *a priori* knowledge of (estimated) transaction execution times, which are difficult to predict in RTDBs [25, 26].

Möenkeberg et al [20] observe that databases thrash under high data contention, which may cause many deadline misses in RTDBs. To avoid thrashing due to data contention, they measure data conflicts and dynamically adjust admission control to prevent thrashing, while improving the response time and throughput. However, transaction deadlines, data temporal consistency, and formal control theoretic approaches are not considered in their work.

Schroeder et al [27] propose a feedback-based approach to determine an appropriate multi-programming level, i.e., the number of transactions allowed to concurrently execute, in a database system to avoid either underutilization or overload. However, in their work, no mathematical database model based on control theory is constructed. The controller design process does not follow standard control theoretic approaches and stability analysis is not performed. They do not consider transaction deadlines and data temporal consistency critical in RTDBs. Also, QoS adaptation is not considered.

Our QoS adaptation scheme is similar to APPROXIMATE [29] that applies the milestone approach [13] to monotonically improve the accuracy of query answers, while returning an approximate answer to meet the query deadline. Another option is database sampling [21] in which more data can be sampled to improve the accuracy of answers to real-time queries. These work, however, do not consider feedback control.

System identification has been used to model dynamics of software systems including the Apache web server, MPEG player, real-time middleware, and email server [15, 3, 19, 23]. These work, however, are not directly applicable to RTDBs, because these systems do not consider RTDB-specific issues such as transaction aborts/restarts and the quality of query/transaction processing [29]. Thus, the

control model, QoS metrics, and the QoS management techniques are different.

7 Conclusions

RTDBs can be employed in a number of data-intensive real-time applications such as agile manufacturing and target tracking. It is challenging to manage the RTDB performance due to data/resource conflicts. In this paper, we propose a new RTDB control model that effectively captures RTDB-specific data/resource contention requiring no knowledge of transaction execution times. Based on the model, we design and tune a utilization controller. According to the control signal, i.e., the required total arrival rate adjustment, our QoS management and admission control schemes adapt the workload, if necessary, to support the target utilization. In a simulation study, we show that our approach can support the target utilization, while substantially improving the success ratio compared to the tested baselines under overload. In the future, we will investigate a more advanced RTDB control model and QoS adaptation/admission control techniques to further improve the quality of real-time data service.

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