Dynamic Power Management in a Mobile Multimedia System with Guaranteed Quality-of-Service*

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Abstract *– In this paper we address the problem of dynamic power management in a distributed multimedia system with a required quality of service (QoS). Using a generalized stochastic Petri net model where the non-exponential inter-arrival time distribution of the incoming requests is captured by the "stage method", we provide a detailed model of the power-managed multimedia system under general QoS constraints. Based on this mathematical model, the power-optimal policy is obtained by solving a linear programming problem. We compare the new problem formulation and solution technique to previous dynamic power management techniques that can only optimize power under delay constraints. We then demonstrate that these other techniques yield policies with higher power dissipation by over-constraining the delay target in an attempt to indirectly satisfy the QoS constraints. In contrast, our new method correctly formulates the power management problem under QoS constraints and obtains the optimal solution.*

1 INTRODUCTION

With the rapid progress in semiconductor technology, chip density and operation frequency have increased, making power consumption in battery-operated portable devices a major concern. High power consumption reduces battery service life. The goal of low-power design [1]-[4] for battery-powered devices is to extend battery service life while meeting performance requirements. Dynamic power management (DPM) [5] – which refers to the selective shut-off or slow-down of system components that are idle or underutilized – has proven to be a particularly effective technique for reducing power dissipation in such systems.

A simple and widely used technique is the "time-out" policy [5], which turns the component on when it is to be used and turns the component off when it has not been used for some pre-specified length of time. Srivastava et al. [6] proposed a predictive power management strategy, which uses a regression equation based on the previous "on" and "off" times of the component to estimate the next "turn-on" time. In [7], Hwang and Wu have introduced a more complex predictive shutdown strategy that has a better performance. However, these heuristic techniques cannot handle components with more than two ("on" and "off") power modes; they cannot handle complex system behaviors, and they cannot guarantee optimality.

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As was first shown in [8], a power-managed system can be modeled as a **discrete-time Markov decision process** (DTMDP) by combining the stochastic models of each component. Once the model and its parameters are determined, an optimal power management policy for achieving the best power-delay trade-off in the system can be generated. In [9], the authors extend [8] by modeling the power-managed system using a **continuous-time Markov decision process** (CTMDP). Further research results can be found in [10]-[13].

In situations where complex system behaviors, such as concurrency, synchronization, mutual exclusion, and conflict, are present, the modeling techniques in [8]-[10] become inadequate because they are effective only when constructing stochastic models of simple systems consisting of non-interacting components. In [14], a technique based on **controllable generalized stochastic Petri nets (GSPN) with cost** is proposed that is powerful enough to compactly model a power-managed system with complex behavioral characteristics. It is indeed easier for the system designer to manually specify the GSPN model than to provide a CTMDP model. Given the GSPN model, it is then simple to automatically construct an equivalent (but much larger) CTMDP model. The policy optimization algorithms in [8]-[10] can thereby be applied to calculate the minimum-power policy for the power-managed system with delay constraints.

Many Internet applications such as web browsing, email, and file transfer are not time-critical. Therefore, the Internet Protocol (IP) and architecture are designed to provide a "best effort" quality of service. There is no guarantee of when the data will arrive or how quickly it will be serviced. However, this approach is not suitable for a new breed of Internet applications, including audio and video streaming, which demand high bandwidth and low latency when used in a two-way communication scenario such as net conferencing and net telephony, for example. The notion of guaranteed quality of service (QoS) comes with the emergence of such distributed multimedia systems. QoS represents the set of those quantitative and qualitative characteristics of a distributed multimedia system necessary to achieve the required functionality of an application [15].

Three parameters are widely used to quantitatively capture the notion of QoS in distributed multimedia systems [15]. These parameters are:

1. *Delay (D):* The time between the moment a data unit is received (input) and the moment it is sent (output).
2. *Jitter (J):* The variation of the delays experienced by different data units in the same input stream. In mathematical formulation, *J* can be defined as the variance of the delay or the standard deviation of the delay.
3. *Loss rate (L):* The fraction of data units lost during transport.

In this paper, we propose a framework for the Power and QoS (PQ) management (PQM) of portable multimedia system clients. The PQ manager performs both power management and QoS management. The multimedia (MM) client is modeled as a controllable GSPN with cost (e.g., power, delay, jitter, and loss rate). Given the constraints on delay, jitter, and loss rate, the optimal PQ management policy for minimum power consumption can be obtained by solving a linear programming (LP) problem.

Compared to previous research work on power management and multimedia systems, our work has the following innovations:

1. This is the first work to consider power and QoS management in a distributed MM system.
2. We present a new system model of an MM client. This new model accurately captures the different behaviors of the MM and normal applications running on the MM client.
3. The proposed optimization solution considers not only power dissipation and delay, but also jitter and loss rate. We managed to formulate this problem as a linear programming problem by making appropriate transformations on the jitter and loss rate constraints.

This remainder of the paper is organized as follows. Section 2 presents the system modeling techniques for the PQ-managed MM client. Section 3 introduces the policy optimization method. Sections 4 and 5 give the experimental results and conclusions.

2 MODELING THE PQ-MANAGED CLIENT

Figure 1 shows a simplified view of a distributed MM system with QoS management [17]. The system consists of three components: an MM server with a database of multimedia objects and a database of QoS information, a transport system that mainly consists of a network of communication channels, routers, and switches, and an MM client, which can be a portable personal computer, pocket PC, or other mobile multimedia devices.

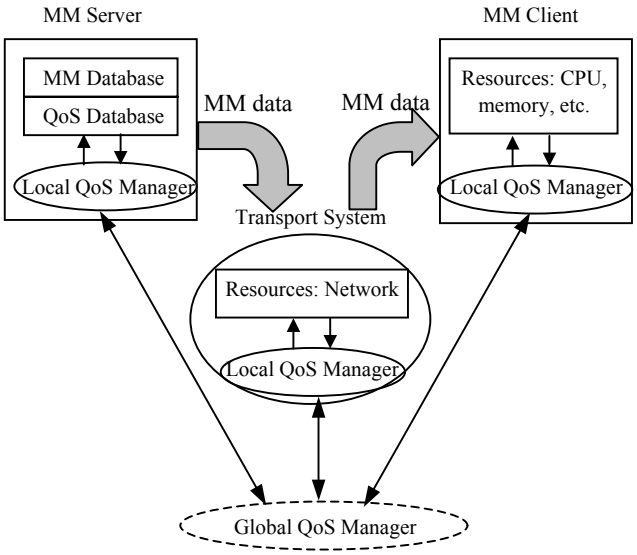


Figure 1 QoS managed, distributed multimedia system.

Each component of the multimedia system has its own local QoS manager. The global QoS manager controls the QoS negotiation and renegotiation procedure among the components. The procedure can be briefly described as follows. The local QoS manager reports the available local resources to the QoS manager. The global manager computes the QoS that each component needs to deliver based on the available resources and sends the requirement to the local manager. The local manager uses its available resources to enforce the local QoS requirement and keeps on monitoring the local QoS. If there is a local QoS violation, the local manager sends a request to the global manager, who will respond to the request by either re-allocating the local QoS requirement among the different components or negotiating with the user to adopt a degraded global QoS.

Because low power design is targeted to electronic components with a limited power source, we focus on PQ management for the MM client, the assumption being that the MM server has a large (or infinite) power source. In this context, the "local QoS manager" of the MM client in Figure 1 will be referred to as the "local PQ manager."

Only components related to the PQ management problem are shown in Figure 1. Although the GSPN formalism can model complex systems with multiple, interacting service providers, in this paper, we use a simple system with a single service provider. This is because the focus of this paper is on power and QoS management, not on complex system modeling. For an example of using GSPN to model a complex power-managed system with multiple interacting service providers, please refer to [14].

Figure 2 gives a simplified block diagram of our PQ-managed client.

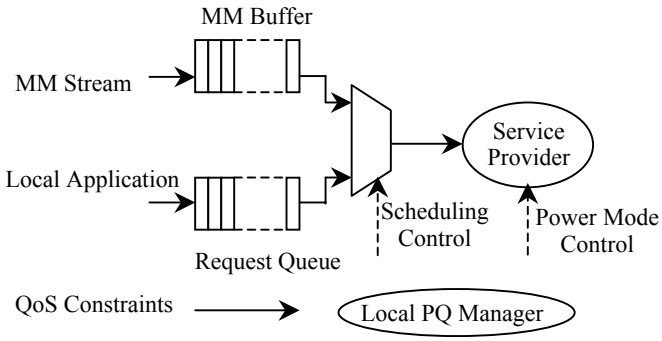


Figure 2 Block diagram of a PQ-managed MM client.

As shown in Figure 2, the MM client consists of a service provider (SP) that may be a CPU, a DSP, or an array of hard disks. The SP provides services (e.g., computing, processing, communication, data retrieval, and storage) for service requests coming from applications running on the MM client. We divide the applications into two categories: the MM applications and the "other" applications. We separate the MM applications because of their distinguishing features as explained below:

1. The distribution of request inter-arrival times is non-exponential, which requires special treatment during the modeling process;
2. The QoS requirement is only applicable to the MM application;
3. The priority of the service requests from the MM application is usually higher than those from "other" applications.

Figure 3 shows the top level GSPN model for the MM client. It is divided into three major parts:

1. MM service requester (SR) and service queue (SQ): The MM SR is used to model the statistical behavior of the input MM

stream, and the MM SQ is used to model the behavior of the MM buffer. The GSPN model is shown in Figure 4.

2. Local SR and SQ: These are used to model the behavior of the request generation and as a buffer for other applications. The GSPN model is shown in Figure 5.
3. The task scheduler (TS) and service provider (SP): The TS is used to represent the mechanism for selecting what request is to be processed next. The SP model captures the power/performance characteristics of the actual service provider.

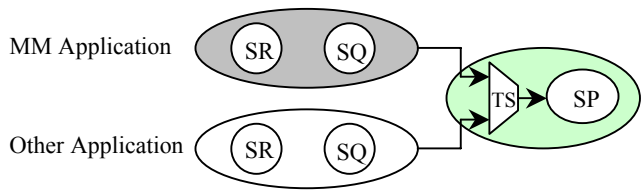


Figure 3 Top-level GSPN model for the MM client.

We assume that the unit inter-arrival time for the MM stream can be any distribution. Since exponential distribution is required by the GSPN modeling technique, we use the "stage method" [14] to approximate the MM stream distribution by using a three-stage SR model. The MM SR consists of places P_{MMa}, P_{MMb}, P_{MM1}, and P_{MM2} and activities μ_1, μ_2, μ_3, α_1 ($\beta_1 = 1-\alpha_1$), and α_2 ($\beta_2 = 1-\alpha_2$), connected as shown in Figure 4. Given a distribution of the input inter-arrival time of the MM stream, we can obtain the values of μ_1, μ_2, μ_3, α_1, and α_2 by curve fitting. P_{MMBuf} represents the MM SQ.

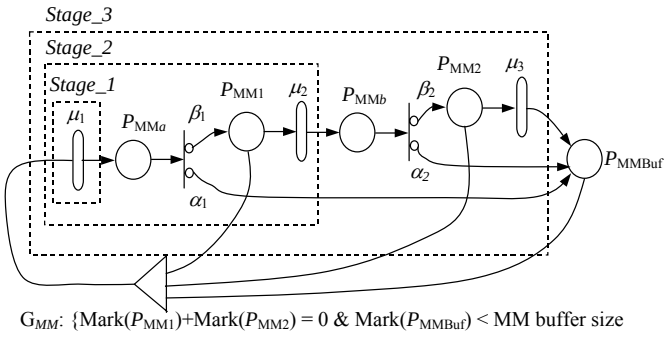


Figure 4 GSPN model for the MM SR and SQ.

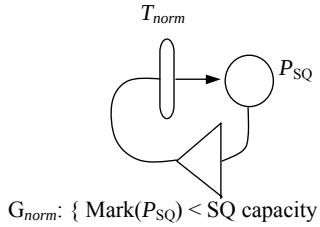


Figure 5 GSPN model for the local SR and SQ.

To emphasize the difference between MM applications and "other" applications (which we will denote as *normal* applications from now on), we assume that the request inter-arrival time for the normal applications is exponentially distributed. The GSPN model for these applications is shown in Figure 5.

Figure 6 shows the GSPN model of a task scheduler and a simple SP, which has two different power modes: active (denoted as "*a*") and sleeping (denoted as "*s*"). When the SP is in active mode, it can be processing MM applications, which is denoted by mode (*a*, MM), or processing normal applications, which is denoted by mode (a, norm).

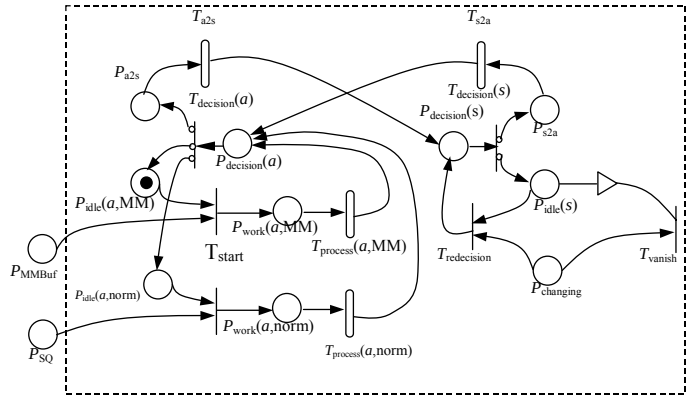


Figure 6 GSPN model for the SP and TS.

To illustrate how the GSPN in Figure 6 works, assume that the initial state of the system is active-idle and waiting for a MM application and the MM buffer is empty. When a token arrives at P_{MMBuf}, which means that an MM request has arrived, the token in place $P_{idle}(a,MM)$ moves to place $P_{work}(a,MM)$, which represents the state of the SP when it is active and servicing an MM request. The duration t of this service is decided by the timed activity $T_{process}(a,MM)$. After time t, the token in $P_{work}(a,MM)$ moves to place $P_{decision}(a)$, which represents the state of the SP when it is active and accepting a command from the PQ manager. After a very short time, the token in $P_{decision}(a)$ moves to P_{a2s}, $P_{idle}(a,MM)$, or $P_{idle}(a,norm)$ with probability a_1, a_2, and $1-a_1-a_2$, respectively. In the controllable GSPN, these probabilities are the controllable case probabilities of activity $T_{decision}(a)$, which are to be optimized. The rest of the system works in a similar way. The mechanism of task scheduling is modeled by the immediate activity $T_{decision}(a)$.

The PQ manager reads the states of all system components and sends commands to control the task scheduling and the SP state transition.

The GSPN model of the MM client is then automatically transformed into a continuous-time Markov decision process (CTMDP). The optimal PQ management policy is then solved based on this CTMDP.

3 POLICY OPTIMIZATION

The input to our policy optimization algorithm is the required QoS, which can be represented by (**D**, **J**, **L**). In real applications, D (delay) may be specified in time units; J (jitter) may then be specified in time units or square of time units; L (loss rate) may be specified in real numbers. However, we do not use these constraints directly in our policy optimization process. Instead, we convert D and J from the time domain to an integer domain related to the number of requests waiting in the queue. Next we remove the L constraint by buffer size estimation based on the relation between L, D, and J. Finally we formulate a linear programming problem that can be solved for an optimal PQ management policy, which achieves minimum power consumption under the QoS constraints.

3.1 Transforming the D and J Constraints

We use the average number of waiting requests in the queue to represent the average request delay (D) and the variance of the number of waiting requests in the queue to represent the request delay variance (J). We use the probability that the queue is full to represent the loss rate (L). The justification for these representations is the following theorem, which shows the relationship between the request delay and the number of waiting requests in the queue.

Theorem: *In a PQ-managed system, if the request loss rate is small enough, then $D = Q \cdot \lambda$, where D is the average request delay, Q is the average number of waiting requests in the queue, and λ is the average incoming request speed. Furthermore, during any time period of length T, $E_T(d) = E_T(q) \cdot T / X$, where $E_T(d)$ and $E_T(q)$ denote the average request delay and average number of waiting requests in the queue during time T, and X is the number of incoming requests in this system during time period T.*

3.2 Estimating the Buffer Size

For the MM client, allocating too much memory for the MM buffer is unnecessary and wasteful. However, we have to make sure that the MM buffer is big enough so that the SP does not need to provide unnecessarily fast service to achieve the given loss rate constraint, which would in turn result in undesired power consumption. Table 1 shows a simple example. Assume a PQ-managed MM client and a QoS constraint of (D, J, L) = (1.5, 0.9, 0.02). In the first case, we set the size of the MM buffer to 4 and solve the optimal policy under the constraints of D and J. In the second case, we set the size of the MM buffer to 6 and solve the optimal policy under the constraints of the same D and J. Then we simulate both policies using UltraSAN and obtain the simulated value of D, J, L, and power consumption (P).

Table 1 Power comparison for systems with different buffer sizes.

Buffer size	D	J	L	Power
4	1.23	0.75	0.02	2.08
6	1.5	0.9	0.02	1.49

From the above table we can see that the system with a buffer size of 4 consumes 40% more power than the system with a buffer size of 6; however, in the former case, the D and J values are smaller than the given constraints. The reason for this is that, with insufficient buffer space, the SP has to spend extra power to provide a faster service speed. This experiment also shows that D, J, L, and the size of the MM buffer are not mutually independent. Given three of them, we can estimate the fourth one. More precisely, their relationship can be formulated by equations (1) to (4), where p_i is the probability that there are i requests waiting in the queue (MM buffer) and m and v are the mean value and the variance of the waiting requests in the queue.

$$\sum_{i=1}^{n} i \cdot p_i = m \tag{1}$$

$$\sum_{i=0}^{n} (i-m)^2 \cdot p_n = v \tag{2}$$

$$\sum_{i=0}^{n} p_i = 1 \tag{3}$$

$$0 \le p_i \le 1,\ i=1, \ldots, n. \tag{4}$$

We are interested in finding the minimum buffer size n that is needed to avoid unnecessary power consumption due to over constraints on D and J. This problem can be solved as follows:

$$Min.\ n$$

$$\text{Subject to: } \sum_{i=1}^{n} i \cdot p_i = D, \tag{4.5}$$

$$\sum_{i=0}^{n} (i-m)^2 \cdot p_n = J, \tag{4.6}$$

$$\sum_{i=0}^{n} p_i = 1, \tag{4.7}$$

$$p_n \le L, \tag{4.8}$$

$$0 \le p_i \le 1,\ i=1, \ldots, n \tag{4.9}$$

We cannot solve above problem exactly. However, after some simplification, we find that if n satisfies inequality relations (4.10) to (4.12), there will be a set of p_i, which satisfies functions (4.5) to (4.9).

$$(n-2)^2 \cdot L \ge J + D^2 - 4 \cdot D + 3, \tag{4.10}$$

$$(n+1) \cdot (n-2) \cdot L \ge m - 2, \tag{4.11}$$

$$(n-2) \cdot (n-1) \cdot L \ge D^2 - 3 \cdot D + 2 + J \tag{4.12}$$

Therefore, we obtain an upper bound on the minimum required buffer size:

$$N_{up} = Max(n_1, n_2, n_3) \tag{4.13}$$

where n_1, n_2, and n_3 are the solutions of equations (4.10), (4.11) and (4.12). If the allocated buffer size is larger than N_{up}, there will not be extra power waste due to over-constraining D and J. Note that this buffer size estimation is independent of the incoming-data rate and the system service rate, because we assume that the given QoS constraint (D, J, L) can always be satisfied by the optimal policy.

We have performed experiments to verify our buffer estimation method, and we set $J = 1.5$, $L = 5\%$. By using different D values between 1 and 3.5, we estimate the minimum buffer size, N_{up}, using (4.13). Figure 7 shows the comparison between the estimated value and the real value that is obtained by simulation. The results show the accuracy of our method.

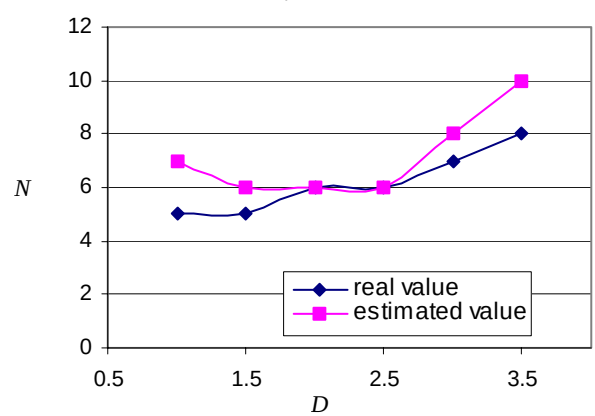


Figure 7 Comparison of real value and estimated upper bound.

3.3 Policy Optimization by Linear Programming

The PQ management problem is to find the optimal policy (set of state-action pairs) such that the average system power dissipation

is minimized subject to the performance constraints for the traditional application and the QoS constraints for the MM application.

First we give the definition of some variables. The reader may refer to [14] regarding how to calculate some of the variables from a given CTMDP model.

$p_{ij}^{a_i}$: Probability that the next system state is j if the system is currently in state i and action a_i is taken

$\tau_i^{a_i}$: Expected duration of the time that the system will be in state i if action a_i is chosen in this state

$x_i^{a_i}$: Probability that the next state of the system will be i and action a_i will be taken if a random observation of the system is taken

pow_i: System power consumption in state i

q_MMBuf_i: Number of unprocessed data in the MM buffer

ene_{ij}: Energy needed for the system to switch from state i to state j

A_i: Set of available actions in state i

Our LP problem is formulated as follows:

LP1:

$$\text{Min}_{\{x_i^{a_i}\}} \sum_i \sum_{a_i} x_i^{a_i} (pow_i \cdot \tau_i^{a_i} + \sum_j ene_{ij}^{a_i} \cdot p_{ij}^{a_i}) \qquad (4.14)$$

$$\text{subject to} \quad \sum_{a_i} x_i^{a_i} - \sum_j \sum_{a_i} x_j^{a_i} \cdot p_{ji}^{a_i} = 0 \quad i \in S$$

$$\sum_i \sum_{a_i} x_i^{a_i} \tau_i^{a_i} = 1$$

$$x_i^{a_i} \geq 0 \quad \text{all } i, a_i$$

$$\sum_i \sum_{a_i} x_i^{a_i} \cdot q\_MMBuf_i \cdot \tau_i^{a_i} < D$$

$$\sum_i \sum_{a^i} x_i^{a_i} \cdot (q\_MMBuf_i - D)^2 \cdot \tau_i^{a_i} < J \qquad (4.15)$$

Equation (4.15) gives the constraint on jitter, which is represented by the jitter of q_MMBuf_i. Note that the left hand side of (4.15) does not give the exact jitter of q_MMBuf_i, which is:

$$\sum_i \sum_{a^i} x_i^{a_i} \cdot (q\_MMBuf_i - \sum_i \sum_{a_i} x_i^{a_i} \cdot q\_MMBuf_i \cdot \tau_i^{a_i})^2 \cdot \tau_i^{a_i} \qquad (4.16)$$

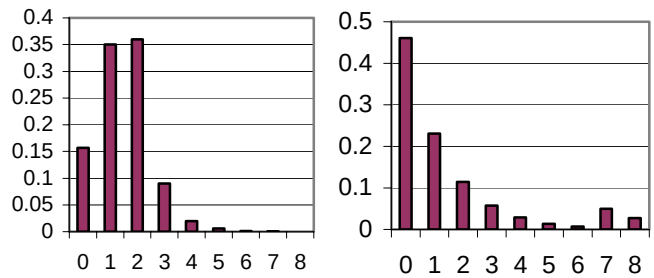
Equation (4.16) contains nonlinear terms. For computational efficiency, we opted to use an approximation of jitter so that the resulting mathematical program remains linear.

Proposition: For any set of $\{x_i^{a_i}\}$ that satisfies (4.15) the value of (4.16) is less than J.

Proof: To minimize $\sum_i \sum_{a^i} x_i^{a_i} \cdot (q\_MMBuf_i - m) \cdot \tau_i^{a_i}$, we know that: $m = \sum_i \sum_{a_i} x_i^{a_i} \cdot q\_MMBuf_i \cdot \tau_i^{a_i}$. Therefore, $\forall m$, (4.16) gives the smallest value. ■

From the above proposition we know that for any policy that satisfies constraint (4.15), the real jitter of q_MMBuf_i using this policy is less than constraint J. Hence we can use (4.15) instead of (4.16).

Figure 8 shows an illustration of q_MMBuf_i distribution when the system is using the PQ-optimized policy and the PD-optimized policy (which in previous work, optimizes power only under delay constraint). In this example, we set the MM buffer size to 8. The average length of the MM buffer is the same for both policies. The power consumption of the system using the PD-optimized policy is 25% less than that of the system using the PQ-optimized policy. However, the q_MMBuf_i jitter and loss rate of the system using the PD-optimized policy are 3X and 1000X larger than those of the system using the PQ-optimized policy. In the experimental results, we can achieve the same q_MMBuf_i jitter for the system using PD-optimized policy by over-constraining the average delay and therefore consuming more power.



q_MMBuf_i distribution using PQ-optimized policy

q_MMBuf_i distribution using PD-optimized policy

Figure 8 Comparison of q_MMBuf_i distribution.

Notice that in LP1, only the QoS constraint for the MM application was included. We can easily add the performance constraint (i.e. delay) for the normal applications.

4 EXPERIMENTAL RESULTS

Our target system is a simplified model of a client system in a distributed MM system. System details are as follows. The SR has only a request generation state. The average inter-arrival time of a traditional request is 50ms. The SQ capacity is 3. The average inter-arrival time of the MM data is 20ms.

The SP has two *p_modes*: high-power mode and low-power mode. It takes 0.2J energy to switch from high-power mode to low-power mode and 0.5J energy to switch from low-power mode to high-power mode. To simplify the model, we assume that the time needed for switching is small enough to be neglected. In both power modes, the SP can process both the MM applications and the normal applications, but with different power consumptions and speeds. There is also another scenario in which the SP is not processing any applications. In this case, the service speed of the SP is 0, and only a very small amount of power is consumed. Therefore, in our target system, there are three a_modes: MM, normal, and idle. Table 2 and Table 3 give the SP power consumption and average service time for each combination of p_mode and a_mode. Here we assume that the high-power mode is designed specifically for MM application. For example, in this mode a floating-point co-processor is used so that the service speed of the MM application increases significantly.

Table 2 SP power (w) for each (p_mode, a_mode) pair.

	MM	Normal	Idle
High power	4	3	2
Low power	2	1.5	1

Table 3 SP service speed (ms) for each (p_mode, a_mode) pair.

	MM	Normal	Idle
High power	5	2	0
Low power	10	2.5	0

Table 4 Comparison between PQ-optimized and PD-optimized policies.

QoS Constraints	PD-optimized			PQ-optimized			ΔP (%)
	Power	D	J	Power	D	J	
(1, 1, 0.1%)	2.15	0.55	0.96	1.95	0.86	0.98	9.3
(1, 1.5, 0.1%)	1.75	0.80	1.46	1.63	1.00	1.49	6.9
(3, 1, 0.1%)	2.15	0.55	0.96	1.92	2.86	0.98	10.7
(3, 1.5, 0.1%)	1.75	0.80	1.46	1.57	2.93	1.50	10.3
(5, 1, 0.1%)	2.15	0.55	0.96	1.72	4.80	0.97	20.0
(5, 1.5, 0.1%)	1.75	0.80	1.46	1.47	3.69	1.46	16.0

In our experiment, because the normal application is not time critical, we set the performance constraint of normal application simply as loss rate ≤ 5%. We use different QoS constraints (D, J, L) for the linear programming problem. We solve LP1 to find the PQ-optimized policy. We use the procedure in [14] to find the PD-optimized policy under the given *D* constraint. If the resulting jitter and loss rate cannot meet the QoS constraints, we decrease D and recalculate the PD-optimized policy until they meet the constraints. The results are shown in

Table 4.

From the above results, we reach the following conclusions:

1. Our method can calculate the PQ-optimized policy for the MM client for given QoS constraints by solving the LP problem only once while the previous DPM method has to obtain the PD-optimized policy for given QoS constraints by solving the LP problem multiple times.
2. Our method can obtain the PQ-optimized policy that matches the given QoS constraints while the previous method can only meet the QoS constraints by over-constraining the delay requirement, which results in larger power consumption.

5 CONCLUSIONS

We have presented a new modeling and optimization technique for power and QoS management in distributed multimedia systems. QoS in this context refers to the combination of the average service time (delay), the service time variation (jitter), and the network loss rate. We model the power-managed multimedia system with guaranteed QoS as a GSPN, and the PQ-optimal policy is obtained by solving a linear programming problem. Because jitter and loss rate are correlated parameters, we could not include both of them into the LP formulation directly. Instead we removed the loss rate constraint from the LP formulation by estimating the maximum size of the queue that stores the MM data. Furthermore, the jitter constraint is a non-linear function of the variables we wanted to optimize. Therefore it could not be directly used in the LP formulation. We were able to substitute the original jitter constraint with another linear constraint, which we mathematically proved to be correct.

Previous methods only consider the delay constraint while obtaining the PD-optimized policy. They can only meet the jitter and loss rate constraints by over-constraining the delay. Compared to these methods, we show that our PQM method can achieve an average of 12% more power savings.

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