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Exhibit B	L. Wang and L. Qian, "MMSEmail: Delivering Emails to Mobile Phone Through MMS," 2009 International Conference on Multimedia Information Networking and Security, Wuhan, China, 2009, pages. 663-666, doi: 10.1109/MINES.2009.104.
Exhibit C	K. Nakatsu, Y. Furuishi and Y. Kanagawa, "Damping Control of Small Actuator for Moving Heads of VCRs," in IEEE Transactions on Consumer Electronics, Volume 39, Issue 2, pages 71-76, May 1993, doi: 10.1109/30.214810.

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Profit-Aware Server Allocation for Green Internet Services

Publisher: IEEE Cite This PDF

Michele Mazzucco ; Dmytro Dyachuk ; Marios Dikaiakos All Authors

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Abstract

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II. The Model

III. Analysis

IV. Power Usage Estimation

V. Allocation Policy

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Abstract:
A server farm is examined, where a number of servers are used to offer a service to impatient customers. Every completed request generates a certain amount of profit, running servers consume electricity for power and cooling, while waiting customers might leave the system before receiving service if they experience excessive delays. A dynamic allocation policy aiming at satisfying the conflicting goals of maximizing the quality of users' experience while minimizing the cost for the provider is introduced and evaluated. The results of several experiments are described, showing that the proposed scheme performs well under different traffic conditions.

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SECTION I.
Introduction

In recent years large investments have been made to build data centers, or *server farms*, purpose-built facilities providing storage and computing services within and across organizational boundaries. A typical server farm may contain thousands of servers, which require large amounts of power to operate and to keep cool, not to mention the hidden costs associated with data centers' carbon footprint and water consumption for cooling purposes [1]. On the other hand, the increasing use of the Internet as a provider of services and a major information media have changed significantly, especially over the last ten years. Expectations in terms of performance and responsiveness have markedly grown. For example, Google reports that an extra 0.5 seconds in search page generation entails degraded user satisfaction, with a consequent 20% traffic drop, while trimming the page size of Google Maps by 30% resulted in a 30% traffic increase [2], [3]. Hence, the development of 'green' data centers, *i.e.*, data centers that are energy efficient, is a challenging problem for service providers as they operate under stringent performance requirements. Consequently, it is very important to devise strategies aiming at reducing the power consumption while maintaining acceptable levels of performance.

Unfortunately, despite considerable effort in designing servers whose power consumption is proportional to their utilization [4], the reality is that the amount of power consumed by an idle server is about 65% of its peak consumption [5], as existing hardware components offer only limited controls for trading power for performance. Thus, the only way to significantly reduce data centers' power consumption is to improve the server farm's utilization, *e.g.*, by tearing down servers in excess. Therefore, we propose and evaluate a strategy that aims at maximizing the overall performance while minimizing the number of required servers. Under suitable assumptions about the nature of user demand, it is possible to explicitly evaluate the effect of a particular server allocation on the achievable revenue. Hence, we derive a numerical algorithm for computing the optimal number of servers required for handling a certain user demand. The model considers limited user patience time and the fact that servers energy consumption depends on servers' utilization. The computational costs of the decision making are extremely low and the algorithm can be used on-line as a part of a dynamic allocation policy.

The problem of reducing energy consumption of server farms can be approached from different angles. Improving energy efficiency for servers by means of dynamic scaling of the CPU frequency has been addressed in several papers, *e.g.*, [6], [7]. An alternative solution consists of switching off servers in excess. The most closely related work can perhaps be found in [8] and [9]. The former discusses a queuing model for controlling the energy consumption of service provisioning systems subject to Service Level Agreements. However, while Chen et al. take into account the cost for smaller mean time between failures (MTBF) when powering up/down some servers, the cost function they propose does not consider the time and energy wasted during state changes, nor the cost for failing to meet the promised quality requirements. Hence, the taken decisions could be either too performance

oriented or too energy-efficiency oriented. [9], instead, discusses a problem similar to that we attack in this paper. However, in that paper the authors assume that clients have no patience, while they do not consider the fact that servers consume energy without producing any revenue during system reconfigurations. Finally, since running too many servers increases the electricity consumption while having too few servers switched on requires running those servers' CPUs at higher frequencies, some hybrid approaches have been proposed, *e.g.*, [6].

The rest of the paper is structured in the following way. In the next section we introduce the system model. Section III contains the mathematical analysis. The model for power consumption estimation is discussed in Section IV, while the resulting policy is introduced in Section V. A number of experiments are presented in Section VI. Finally, we conclude the paper in Section VII with a summary and some remarks.

SECTION II.
The Model

A server farm is a collection of servers interconnected by high-speed, switched LANs that hosts content and runs applications (or services) accessed over the Internet. In this paper we focus on server farms designed according to the dedicated architecture, where a web application is hosted on a set of physical servers (see, for example, [10]) and the provider can change the number of servers allocated to run each service in order to react to traffic changes. Once a decision about how to partition the available servers has been made, it is possible to treat each subsystem (*i.e.*, service) in isolation of each other. Therefore, in the following we tackle the problem of maximizing the revenue of a single subsystem (service) only.

Now, assume that q (identical) servers have been allocated to queue i. Among those q servers, h are running and capable of serving incoming user demand (*jobs*, from now on), while the remaining $(q-h)$ are switched off in order to save energy. In this context, the term 'switched off' means that the server can not perform any useful work and it does not consume any electricity. A maximum of m jobs can be processed in parallel on each server without significant interference–this limit being imposed by the number of available threads or processes. This is modelled by assuming that there are m parallel servers on each physical machine or core, and thus a total of $S = qm$ servers are available, while $n = hm$ are running. If n jobs are currently in execution, further requests are temporarily parked into an external first-in-first-out (FIFO) queue whose size is assumed to be infinite. If, once a server has finished processing a request, the queue is empty, the server begins to idle (*i. e.*, it consumes energy without generating any profit). Otherwise, it removes the leading job from the waiting queue and starts processing it. Every processed request generates some profit. For example, it can be a profit coming from advertisements or from sales (in case of online merchants, such as Amazon). While in the first case advertising agencies usually pay for each impression (*i.e.*, display of an add), in the second case the profit from each request can be estimated as follows. Suppose that every 10,000 views generate 10$ of revenue from sales. Hence, we can state that on average each request brings 0.01 cents. It is worth stressing that companies like eBay employ more complex revenue models. However, using simple transformations such as dividing gross income over the number of requests, one can easily estimate the average profit brought by every request.

Since running servers consume electricity, which costs $r$$ per kWh, the provider dynamically decides how many servers to run by means of a 'resource allocation' policy. The objective is to find the optimal number of servers, n,

that should be switched on in order to optimize the provider's profit. The extreme values, $n = 0$ and $n = S$, correspond to switch respectively off, or on, all available servers. Given that the amount of running servers should change in response to changes in the user demand, the problem is how to estimate the best n. We assume that data is widely replicated, hence switching some servers off does not affect service availability. However, since lost jobs do not generate any revenue, the provider should ensure that the time users wait for their requests to be served does not exceed their patience. Otherwise the clients will start aborting their requests, *e.g.*, by clicking a Stop button in their browsers, see Figure 1.

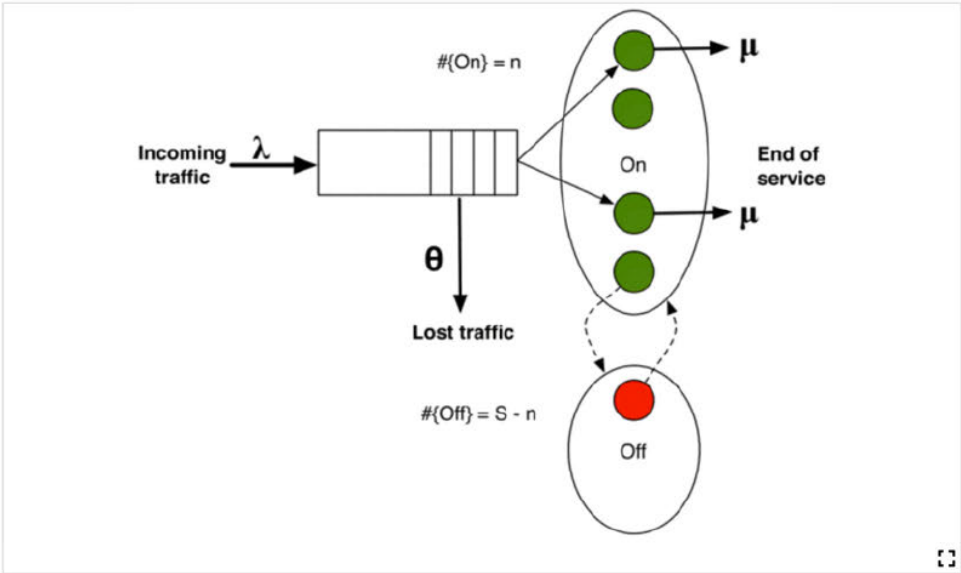

Fig. 1. System model. Jobs whose average job size is $1/\mu$ enter the system at rate λ and abandon the system at rate θ while waiting.

During the intervals between consecutive policy invocations, the number of running servers remains constant. Those intervals' which will be referred to as 'observation windows', are used by the controlling software to collect the traffic statistics used by the allocation policy at the next decision epoch.

While different metrics can be used to measure the performance of a computing system, as far as the service provider is concerned, the performance of the server farm is measured by the average revenue, R, earned per unit time. That value can be estimated as

$$R = cT - rP, \tag{1}$$

View Source

where c is the income generated by each completed job, T is the system's throughput, and P is the total average power consumed by powered up servers. c is a parameter of the model, while the formula for computing T and P are discussed in Sections III and IV. For the following it will be convenient to indicate explicitly the dependency of Equation (1) on the parameter n by introducing the notation

$$R = r(n), \tag{2}$$

View Source

where $r(n)$ stands for the right-hand side of (1).

It is worth noting that although we do not make any assumption about the relative magnitudes of charge and cost parameters, the most challenging case is when they are close to each other. If the charge for executing a job is much higher than the provisioning cost, one could guarantee a positive, but not optimal, revenue by switching on all servers, regardless of the load. On the other hand, if the charge is smaller than the cost, than it would be better to switch all servers off.

SECTION III.
Analysis

Suppose that n servers have been allocated to serve incoming traffic. Jobs enter the system according to an independent Poisson process with rate λ. Operating servers accept one job at a time, with the service times, or 'job size', being exponentially distributed with mean $1/\mu$. Hence, one might try to model the system as an $M/M/n$ queue (see [11] for more details) with the offered load being $\rho = \lambda/\mu$ and with the stability condition being $\rho < n$. Unfortunately, this system, also called Erlang-C (or delay), does not acknowledge abandonment; thus it either distorts or completely fails to provide important information.

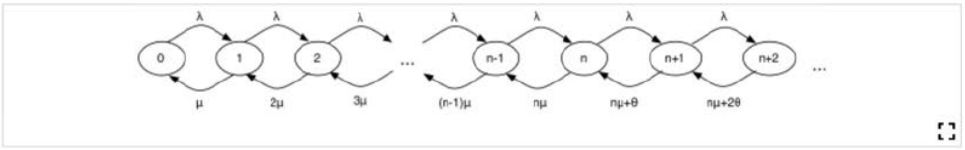

Fig. 2. State transition diagram.

In this work we do allow customers abandonment by assuming that a time-out policy is in operation: if a job entering the system does not acquire a server before its time-out period expires, the job is terminated and leaves the system without generating any revenue. This can be used to model HTTP timeouts, as well as impatient customers. Impatient customers are of particular importance, as [12] reports that 75% of people would not go back to a web site that took more than 4 seconds to load. HTTP time-outs are in practice of fixed length, while users' patience is not. For the purposes of analytical tractability, we assume that both the user's patience and HTTP time-outs are i.i.d random variables distributed exponentially with mean $1/\theta$, with θ being referred to as the *abandonment rate*. The extreme values, $\theta = 0$ and $\theta = \infty$, correspond to jobs with no, or infinite patience. Hence, the appropriate queueing models would be $M/M/n/n$ and $M/M/n$ respectively [11]. Also, we assume that the patience variables are independent of all other model elements, namely arrival and service rates.

The first step to computing Equation (1) is the steady state analysis of the Markov chain associated with the model sketched in Figure 1, see Figure 2. A tractable way to model this system is the $M/M/n+M$ queue, also known as Erlang-A (where the 'A' stands for 'Abandonment') [13]. The main difference between the Erlang-A and Erlang-C models is that the queue never grows unbound in the Erlang-A model, as jobs are allowed to leave. Moreover, jobs abandonment reduces workload only when needed, *i.e.*, when the load is high. The implication is that fewer servers are needed to guarantee the same level of performance under Erlang-A, compared to the traditional Erlang-C. This observation is very important because in this paper we focus on highly loaded (and potentially overloaded) systems, as our goal is to switch off servers in excess while serving as many customers as possible.

Now, let L_t be the total number of jobs inside the system at time t, including both queueing and executing requests. Then, $L = \{L_t : t \geq 0\}$ is a state-dependent *Birth-and-Death* process [11]. The instantaneous transition rate from state j to state $(j+1)$ is equal to the arrival rate, $\lambda_j = \lambda, j = 0, 1, \ldots$. The conditional departure rate, *i.e.*, the transition rate from state j to state $(j-1)$, depends instead on the number of operating servers as well as on the number of jobs present.

Hence, we should distinguish between two cases:

1: $j \leq n$. The system behaves like an $M/M/\infty$ queue: all jobs in the system are being served without queueing, jobs leave the system at rate $\mu_j = j\mu$, and $(n-j)$ servers are idle.

2: $j > n$. All servers are busy and $(j-n)$ jobs are queueing. The instantaneous completion rate does not depend on j anymore, while the abandonment rate depends on the current number of jobs in the queue.

Hence, the balance equations can be expressed in terms of p_0, *i.e.*, the probability of the system being empty

$$p_j = \begin{cases} \frac{\rho^j}{j!} p_0 & \text{if } j \leq n \\ \frac{\rho^n}{n!} p_0 \left[\prod_{k=n+1}^{j} \frac{\lambda}{n\mu + \theta(k-n)} \right] & \text{if } j > n \end{cases}. \tag{3}$$

View Source

The only unknown probability is p_0. Steady state for this process exists only if Equation (3) can be normalized, *i.e.*, if $\sum_{j=0}^{\infty} p_j = 1$. From the normalization condition and from Equation (3) we obtain

$$p_0 = \left[\sum_{j=0}^{n} \frac{\rho^j}{j!} + \frac{\rho^n}{n!} \sum_{j=n+1}^{\infty} \prod_{k=n+1}^{j} \left(\frac{\lambda}{n\mu + \theta(k-n)} \right) \right]^{-1}. \tag{4}$$

View Source

Thus, steady state for this Birth-and-Death process always exists, as jobs in excess eventually abandon, ensuring that the queue never grows unbound. To handle the series in Equation (4) it is convenient to introduce the function [13]

$$g(x, y) = 1 + \sum_{j=1}^{\infty} \frac{y^j}{\prod_{k=1}^{j} (x + k)}. \tag{5}$$

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Thus, by means of Equation (5) and the formula for computing the blocking probability in an Erlang-B system with n trunks and traffic intensity ρ, $B(n, \rho)$ [11], [14], after some algebraic manipulations we obtain

$$p_0 = \frac{n!}{\rho^n} \frac{B(n, \rho)}{1 + B(n, \rho) \left[g\left(\frac{n\mu}{\theta}, \frac{\lambda}{\theta}\right) - 1 \right]}. \tag{6}$$

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Having computed the steady state probability of the number of jobs present, it is possible to estimate the probability of abandonment, $P(Ab)$. Denote by $P_j(S)$ the probability that a job finding j other jobs inside the system will eventually get served. Hence, the probability of abandonment of a job finding j other jobs ahead of it is simply $1 - P_j(S)$. Therefore, we can write

$$P_j(Ab) = \begin{cases} 0 & \text{if } j < n \\ \frac{(j+1-n)\theta}{n\mu + (j+1-n)\theta} & \text{if } j \geq n \end{cases}. \tag{7}$$

View Source

Using Equation (7) and the PASTA property (Poisson arrivals see time averages, see [11] for more details), $P(Ab)$ yields to

$$P(Ab) = \sum_{j=0}^{\infty} p_j P_{j-n}(Ab). \tag{8}$$

View Source

Computing Equation (8) from its right-hand side is challenging. However, using Bayes' formula [15] we obtain

$$P(Ab) = P(W > 0)P(Ab|W > 0), \tag{9}$$

View Source

where $P(W > 0)$ is the delay probability, while $P(Ab|W > 0)$ is the conditional abandonment probability.

In order to compute the above probabilities it is useful to express the balance equations in terms of p_n, *i.e.*, the probability that all servers are busy and the queue is empty. Using Equations (3) and (6), p_n yields to

$$p_n = \frac{B(n,\rho)}{1 + B(n,\rho)\left[g\left(\frac{n\mu}{\theta}, \frac{\lambda}{\theta}\right) - 1\right]}. \tag{10}$$

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Hence, Equation (3) can now be written as

$$p_j = \begin{cases} \frac{n!}{j!\rho^{n-j}} p_n & \text{if } j \leq n \\ \frac{(\lambda/\theta)^{j-n}}{\prod_{k=1}^{j-n}\left(\frac{n\mu}{\theta} + k\right)} p_n & \text{if } j > n \end{cases} \tag{11}$$

View Source

By means of Equation (11) and the PASTA property, it is now possible to estimate the delay probability

$$P(W > 0) = \sum_{j=n}^{\infty} p_j = p_n + \sum_{j=n+1}^{\infty} p_j. \tag{12}$$

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Thus, using Equations (5), (11) and (12) we obtain

$$P(W > 0) = A\left(\frac{n\mu}{\theta}, \frac{\lambda}{\theta}\right) p_n, \tag{13}$$

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while, after some manipulations, $P(Ab|W > 0)$ yields to

$$P(Ab|W > 0) = \frac{1}{\rho g\left(\frac{n\mu}{\theta}, \frac{\lambda}{\theta}\right)} + 1 - \frac{1}{\rho}. \tag{14}$$

View Source

N.B. As the size of the server farms grows, the system achieves economies of scale that make it more robust against traffic variability. Hence, while violating the Markovian assumptions about the arrival, patience and service processes affects the average queue length, it does not substantially change the abandonment rate [16].
Having computed the stationary distribution of jobs present and the corresponding probability of abandonment, we can now compute the average number of requests served per unit time. That value can be expressed as

$$T = min(n\mu, \lambda[1 - P(Ab)]). \tag{15}$$

View Source

N.B. The above expression successfully deals with two special cases, *i.e.*, $\theta = 0$, and thus the system would behave as an $M/M/n$ queue, and $\rho > n$.

SECTION IV.
Power Usage Estimation

A number of factors affect the amount of energy consumed by a server. However, the change in the power consumption of a server is mainly due to changes in the CPU utilization. In order to establish and quantify this relation we have measured the amount of energy drawn by a server in the presence of an increasing load. As for an application we have used Word-press, a popular open source application implementing a blog and running on top of the LAMP stack. The server had two Xeon Dual Core CPUs (2.8 Ghz) equipped with 2 Gb of RAM, 7200 RPM hard drive and 1 Gbps network card, while user demand was generated by Tsung . The workload consisted of clients arriving over time, with each client simulating a typical behavior of a blog reader, such as checking the front page, navigating through the blog, searching for entries containing certain keywords, etc. The load was increased by reducing the interarrival intervals, which were generated according to an independent Poisson process. The measurements reported in Figure 3 show a linear dependency between the CPU utilization and power consumption. The experiment also confirms that idle servers consume a substantial amount of energy (140 Watts in our case). Hence, the average power consumed by a data center per unit time, P, can be estimated as

$$P = ne_1 + \tau(e_2 - e_1), \tag{16}$$

View Source

where e_1 is the energy consumed per unit time by idle servers, e_2 is the energy drawn by each busy server, and τ is the occupancy of the system ($\tau \leq n$)

$$\tau = \left\lceil \frac{T}{\mu} \right\rceil. \tag{17}$$

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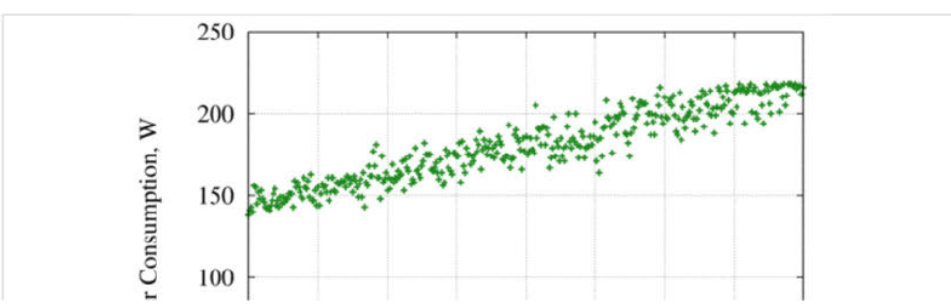

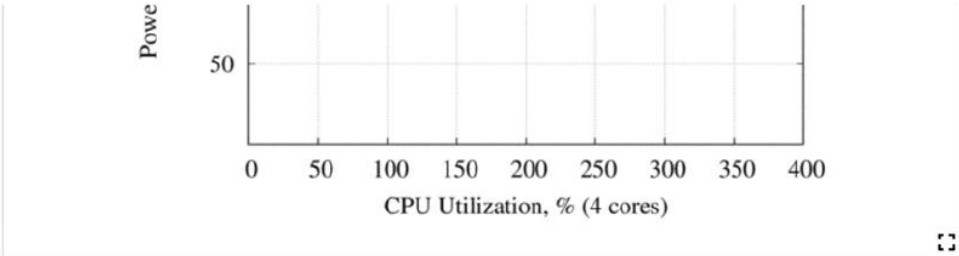

Fig. 3. Measured energy consumption.

SECTION V.
Allocation Policy

Consider now an allocation decision epoch. The state of the subsystem at that instant is defined by the number of servers which are not powered down and by the potential offered load. If the allocation does not change, the expected revenue for the next configuration interval is simply $r(n)$. The alternative is to power on/off some servers. Denote by n' the new number of servers allocated to the queue after reallocation:

1: $n' > n$. Such a decision would increase the system throughput, thus increasing the potential revenue, but it would also increase the amount of energy consumed by the server farm.

2: $n' < n$. Such a decision would decrease the expenditure for electricity, as $(n - n')$ servers would be switched off. However, it would also decrease the overall throughput, thus increasing the probability of jobs abandonment.

Powering servers on/off is not instantaneous, but takes on average k units time. Hence, at every state change there is some waste of time and money because servers changing their state can not serve user demand, but do consume electricity. Also, system's reliability is affected by state changes, as hardware components tend to degrade faster with frequent power on/off cycles than with continuous operation. For example, hard disks have an average lifetime of 40/50,000 on/off cycles [17]. Therefore, each state change involves the following cost

$$Q = \frac{|\Delta n|}{t}\left(\sum_{i=1}^{l} d_i + kre_{max}\right), \tag{18}$$

View Source

where t is the length of the observation windows, $|\Delta n|$ is the number of servers that are switched on/off, e_{max} is the power consumed per unit time during state changes, k is the average time required to switch a server on/off, d_i is the cost for a hardware component's state change, and l is the number of components.

N.B. One can easily relax the assumption that powering a server up and down takes the same amount of time and consume the same amount of energy.
The expected *change* in revenue resulting from a decision to change the number of running servers can be expressed as

$$\Delta r(n', n) = r(n') - r(n) - Q. \tag{19}$$

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When R is computed for different values of n, it becomes clear that the revenue is a unimodal function of n, *i.e.*, it has a single maximum. That observation implies that one can search for the optimal number of servers to run by evaluating R for consecutive values of n, stopping either when R starts decreasing or, if that does not happen, when the increase becomes smaller than some value ϵ. This can be justified arguing that R is a concave function

with respect to n. Intuitively, the economic benefits of powering more servers on become less and less significant as n increases, while the loss of potential revenues gets bigger and bigger as n decreases. Such a behavior is an indication of concavity. Thus, a fast algorithm of the *binary search* variety suggested by the above observations works as follows:

1) Set with $n_l = 0$ and $n_u = S$;

2) Set $n' = \lceil \lambda/\mu \rceil$. If $n' = 0$, set $n' = 1$. Similarly, if $n' = S$, set $n' = S - 1$.

3) While $n_l < n_u$

   a) Calculate $\Delta r(n'-1, n)$, $\Delta r(n', n)$ and $\Delta r(n'+1, n)$.

   b) If $\Delta r(n'-1, n) \leq \Delta r(n', n) \geq \Delta r(n'+1, n)$, then n' is the best solution. Hence, go to 4.

   c) If $\Delta r(n'-1, n) \leq \Delta r(n', n) \leq \Delta r(n'+1, n)$, then the optimal n is in the interval $n', \ldots, n_u$. Hence, set $n_l = n' + 1$ and go to 3e.

   d) We have $\Delta(n'-1, n) \geq \Delta r(n', n) \geq \Delta r(n'+1, n)$. Hence, the search has to be carried out in the interval $n_l, \ldots, n'$, so set $n_u = n' - 1$ and go to 3e.

   e) Set $n' = \lceil n_l + (n_u - n_l)/2 \rceil$.

4) If $\Delta r(n', n) > 0$, then set $n = n'$. Otherwise, leave the allocation as it is.

Since at every iteration the state space is reduced by a factor of two, $log(S)$ iterations are required in order to find the 'best' n, *i.e.*, the number of servers that maximizes the profit. We have put quotation marks around the word 'best' because such choice might be slightly sub-optimal when the exponential assumptions are violated and S is small (see the remarks at the end of Section III). This policy will be referred to as the 'Adaptive' allocation policy.

Finally, since the state change is not instantaneous, the current window ends immediately if some of the servers are to be switched off (*e.g.*, if $n' < n$) or after all the servers are powered up if $n' > n$.

SECTION VI.
Results

Several experiments were carried out, with the aim of evaluating the effects of proposed scheme on the maximum achievable revenues. We assume the server farm has a Power Usage Effectiveness (PUE), the main metric used to evaluate the efficiency of data centers, of 1.7. That value is computed as the ratio between the total facility power and the IT equipment power. Also, we take indirect costs into account. These include the cost for capital as well as the amortization of the equipment such as servers, power generators or transformers, and account for twice the cost of consumed electricity. Finally, in order to reduce the number of variables, when not specified otherwise, the following features were held fixed:

- 250 servers, configured as described in Section IV, *i. e.*, $S = 1,000$.
- The power consumption of each four core server machine ranges between 140 and 220 W, see Figure 3. In other words, each core from now on server consumes between 35 and 55 W. Since the server farm has a PUE factor of 1.7, the minimum and maximum power consumption are approximately $e_1 = 59$ and $e_2 = 94$ W per server.
- The cost for electricity, r, is 0.1 \$ per kWh.

- The average job size, $1/\mu$, is 0.1 seconds.
- Jobs are not completely CPU bound. Instead, when a server is busy, the average CPU utilization is 70%. In other words, busy servers draw 69.58 Wh, and thus each job costs, for electricity, 2×10^{-7}\$ on average.
- Each successfully completed job generates, on average, 6.2×10^{-6}\$.

It is worth noting that while the size of the server farm might look small, the application logic of the 10th busiest web site in the world, Wikipedia, is hosted on 350 servers having 856 cores, spread across three data centers [18].

A. Stationary Traffic

The first experiment, see Figure 4, is purely numerical. It shows how the number of running servers affects the average earned revenue under different loading conditions. The potential offered load is increased from 30% to 90% by increasing the rate at which new jobs enter the system, from 3,000 to 9,000 jobs per second.

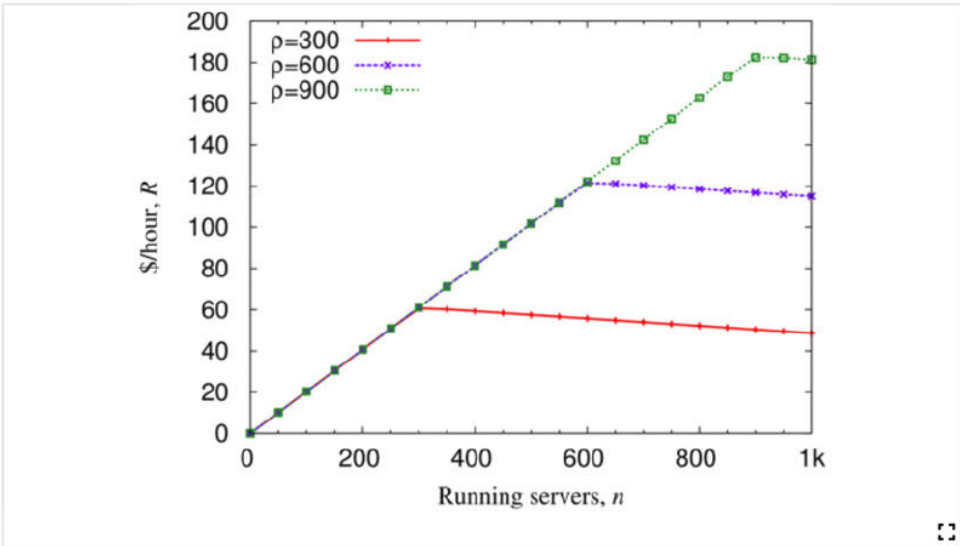
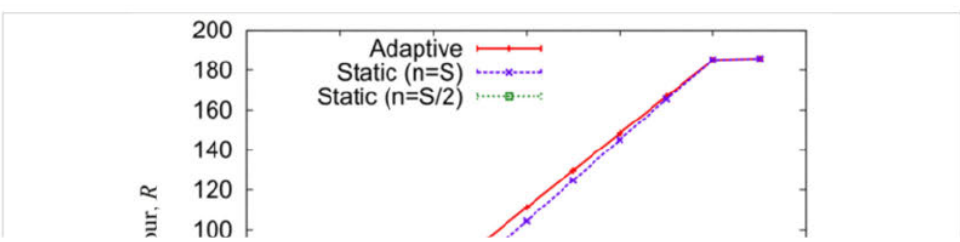


Fig. 4. Revenue as a function of the running servers.

Figure 4 shows that (*i*) in each case there is an optimal number of servers that should be switched on; (*ii*) the heavier is the load, the higher is the optimal number of servers to run, but higher is also the maximum achievable revenue; (*iii*) when $n > n_{opt}$, the system under-performs because the cost of running idle servers erodes revenues, while when $n < n_{opt}$, the system under-performs because it misses potential revenues.

Next, we evaluate the effectiveness of the dynamic allocation scheme via computer simulation. For comparison reasons, two versions of the 'Static' policy, a policy which runs always the same amount of servers, are also displayed. One runs $n = S/2 = 500$ servers, while the other $n = S = 1,000$. We vary the load between 10% and 110% (*i. e.*, the system would be over-saturated without job abandonment) by varying the arrival rate, *i. e.*, $\lambda = 1,000, \ldots, 11,000$ jobs/second. Each point in the figure represents one run lasting 16.5 hours, while servers are reallocated every hour, *e.g.*, the policy described in Section V is invoked every hour. During each run, approximately between 119 (low load) and 653 (high load) million jobs enter the system, while samples of achieved revenues are collected every 1.5 hours and are used at the end of each run to compute the corresponding 95% confidence interval, which is calculated using the Student's t-distribution.



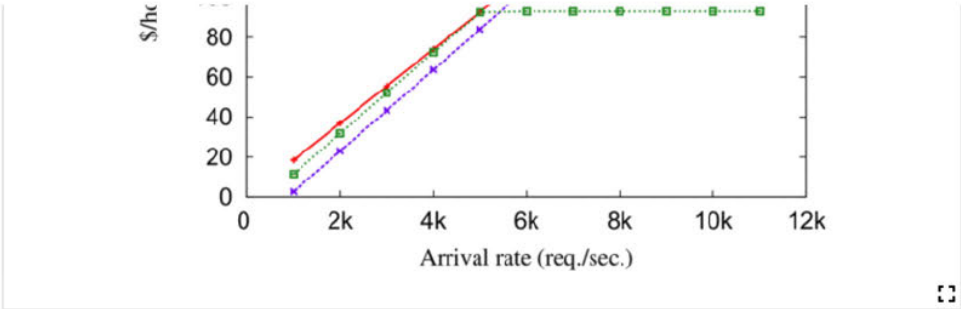


Fig. 5. Observed revenues for different policies.

The most notable feature of the graph plotted in Figure 5 is that the 'Static' policies do not perform well under light load (because of the servers running idle), while the one with parameter $n = S/2$ can not cope with high traffic, thus missing income opportunities. On the other hand, the 'Adaptive' heuristic produces revenues that grow with the offered load. Next, we report the average power consumption. Figure 6 shows that the 'Adaptive' heuristic runs servers only when necessary, thus reducing its carbon footprint as well as the provider's electricity bill.

In the next experiment we evaluate the effects of increased variability on the performance of the 'Adaptive' heuristic by departing from the assumption that the interarrival and patience times are exponentially distributed. Now those parameters are Log-Normally distributed, with the squared coefficient of variation, *i. e.*, the variance divided by the square of the mean, of 2 (interarrival intervals on YouTube have a squared coefficient of variation of 1.7 [19]) and 5, respectively. These changes increase the variances of the interarrival and patience times while preserving the averages, thus making the system less predictable and allocation decisions more challenging.

In Table I we compare the achieved revenue (R), average queue length (L) and the percentage of jobs abandoning the system under the 'Adaptive' policy for different values of S. The system is always loaded at 80% by scaling the arrival rate in proportion to S. From the experiment we observe that while L depends on the variability of the traffic parameters, the achieved revenue and the percentage of jobs leaving do not. Moreover, the system becomes less and less sensible to the distribution of the interarrival intervals and patience times as S increases. This can be explained by observing that large systems can achieve economies of scale which are simply not possible when the number of servers is small. In particular, the behavior of large server farms under heavy load differs from that of Kingman's Law (*i.e.*, delays/job losses are very common under heavy load) in that service quality is carefully balanced with server efficiency.

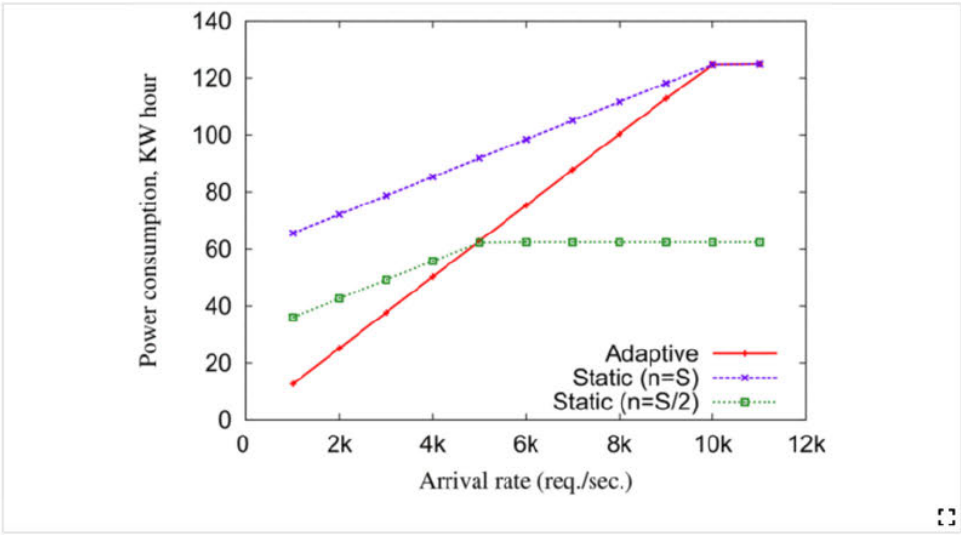


Fig. 6. Observed energy consumption for different policies.

TABLE I Performance of the 'adaptive' heuristic for different parameters.

	$scv(\lambda) = scv(\theta) = 1$			$scv(\lambda) = 2, scv(\theta) = 5$		
S	R	L	% Ab	R	L	% Ab
10	1.45	4.636	1.136	1.44	6.216	1.398
20	2.91	4.602	0.572	2.91	7.040	0.614
50	7.35	11.034	0.547	7.35	17.374	0.514
100	14.75	14.371	0.359	14.76	24.007	0.268
500	74.06	28.467	0.142	74.11	53.349	0.055
1000	148.26	40.651	0.101	148.38	82.370	0.033

B. Sensitivity Analysis

The previous experiments investigated how server allocation decisions and other parameters can affect the revenue. However, in real world scenarios the chances that service providers would have to deal with stationary traffic are extremely rare. In fact, studies of the Wikipedia traces show that throughout the day the incoming traffic can change by as much as 70% [21]. A logical solution to this problem would be reconfiguring the servers pool (by switching servers on/off) according the changes in the load, as we propose in Section V. However, service providers need to estimate the arrival rate for the next configuration interval. Such a prediction might be hard to make if the load is non stationary, and even good forecasting tools might produce results which sometimes differ from the observed values. Forecasting tools range from simply using the last observed value of λ to very complex algorithms requiring significant periods of time for training and considering seasonal and trend components. Instead of benchmarking the proposed approach with various forecasting tools, which would lead to an explosion of the experimental space, in the following we investigate its sensitivity in respect to an error in load prediction. This also can help in choosing the right prediction mechanism in real-world scenarios, as the deployment of certain forecasters may require long training, while simpler ones might exhibit slightly worse prediction quality, while having little or no effect on the ultimate result.

In order to see how various error rates affect the revenue, we introduce an Oracle forecaster which tells the exact arrival rate for the next configuration interval. Then we introduce an error, first 5%, then 10% and finally 20%. Please note that the forecasting values are distributed according to a Laplace distribution with the mean value equal to the actual λ. Thus, for example 5% represents the mean of the absolute differences between actual and predicted values of λ. We have chosen a Laplace distribution because we have observed such a behavior when trying to predict the Wikipedia workload using the double exponential smoothing method. Unfortunately, due to the lack of space we cannot present this data. Also, it is important to note that by combining Oracle with the binary search from section V we obtain the optimal solution in terms of profit maximization.

In the next set of experiments we contrast five different cases: static policy (all servers are switched on), Adaptive heuristic (see Section V) with Oracle forecasting, and Adaptive heuristic with Oracle forecasting making a systematic error of 5%,10% and 20%. In the simulation, a workload which represents a scaled version of the Wikipedia traces is employed. The arrival rate ranges between 2,688 and 5,729 jobs/second, while each simulation run lasts 240 hours (*e.g.*, 10 days).

TABLE II Percentage of lost jobs with respect to error in the prediction

Error	0%	5%	10%	20%
Lost jobs, %	0.01	2.19	4.46	10.54

As shown in Table II, the error in the forecasting has a significant impact on the number of lost jobs. The Oracle behaves almost as good as the static policy which massively over-provisions the system, which in its turn negatively reflects on the amount of consumed energy, see Figure 7, and consequently the revenue, see Figure 8.

At the same time 5% error in the prediction affects the number of lost jobs without significant impact on the other metrics. An increase of the error from 5% to 10% markedly reflects on the number of lost jobs, while the revenue values still stay very close. A jump of the error from 10% to 20% not only increases the number of lost jobs more than twice due to frequent mistakes causing under-provisioning and thus adversely affecting the revenue. Despite the obvious advantage in the power consumption, using forecasting with 20% error is unacceptable due to its low revenue and high percentage of the lost jobs. From the above experiment we can conclude that 5% error in forecasting does not have significant impact on the revenue and energy consumption, while a 10% error still

exhibits results which are markedly superior to the Static allocation policy.

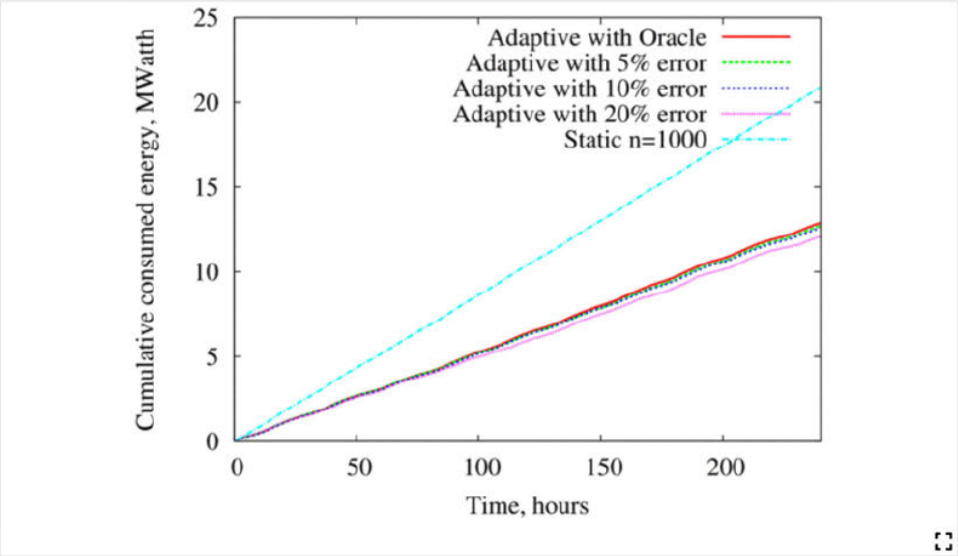


Fig. 7. Cumulative energy consumption.

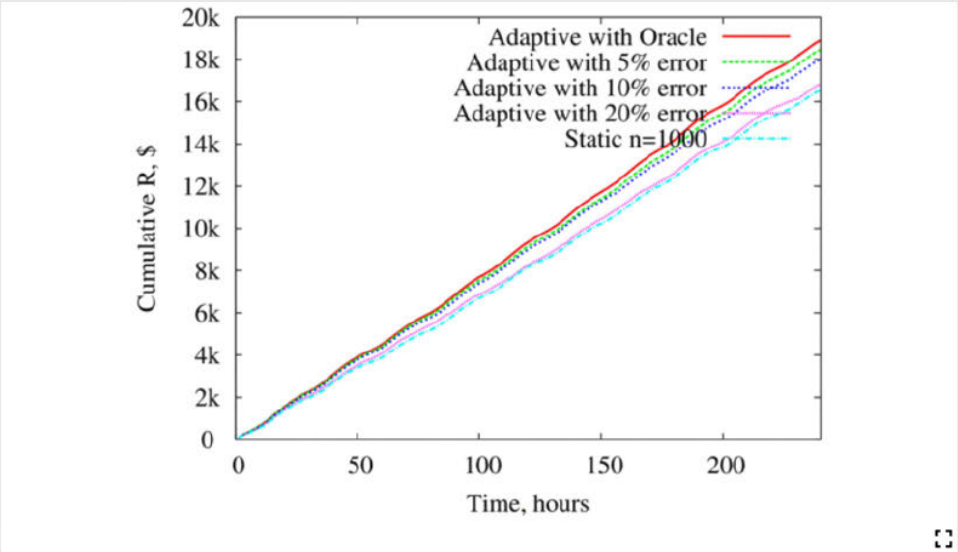


Fig. 8. Cumulative revenue.

SECTION VII.
Conclusions

In this paper we have introduced and evaluated an easily implementable policy for dynamically adaptable Internet services. Under some simplifying assumptions, the numerical algorithm we propose can find the best trade off between consumed power and delivered service quality. We have demonstrated that the number of running servers can have a significant effect on the revenue earned by the provider. The experiments we have conducted show that our approach works well under different traffic conditions, and that our policy is not very sensitive to errors in parameters estimation.

Possible directions for future research include taking into account the trade offs between the number of running

servers, the frequency of the CPUs and the maximum achievable performance, as well as fault tolerance issues.

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MMSEmail: Delivering Emails to Mobile Phone Through MMS

Publisher: IEEE Cite This PDF

Lidong Wang ; Liping Qian All Authors

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Full
Text Views

Abstract

Document Sections

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II. Multimedia Messaging Service

III. MMSEMAIL

IV. Content adaptation broker

V. Conclusion and future works

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Abstract:
With the development of mobile communication, there arises the requirement of ubiquitous access to Internet Email service from small screen terminals such as mobile phones and Pads. This paper proposed a framework, MMSEmail, for delivering Emails to mobile phones through Multimedia Messaging Service (MMS). MMSEmail integrates the functions of Email proxy, content adaptation broker and MMS sender. It not only implements immediate Email delivery by utilizing PUSH mechanism of MMS, but also supports user profile-based content adaptation, spam email filtering and text presentation of Email attachments with special file types as .doc, .rtf and .pdf. Being designed based on the de-facto standards, the framework has great extensibility.

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SECTION I.
Introduction

By December 2008, the data released by MIIT show that the amount of valid mobile phone numbers had reached 641.2 million, among which 253.9 million used mobile packet data services. According to CNNIC, the amount of Chinese netizens surfing the Internet with mobile phones has reached 73.05 million by July 2008, about 28.9% percent of all netizens. The above two statistics show that mobile phone has become one of the most popular means for accessing Internet services, especially for browsing Web pages and processing Emails. Although capabilities of mobile terminals are on the increase, they are still greatly inferior to desktop computers and have various models that quite distinct from computing capability, resolution and color. Email clients for small-screen terminal have been developed and then deployed in some high-end mobile terminals. However, the deficiency in presenting email contents comparing to normal PC, the incapability of processing Email attachments with special file types as. doc,. rtf and. pdf, and the flooding spam emails together cool the enthusiasm of mobile phone users to process email with the limited bandwidth of mobile communication.

Nowadays, Multimedia Messaging Service (MMS) has captured the attention of wireless developers everywhere, especially in China. It allows delivering multimedia content such as text, image, audio, video and their combinations from phone to phone or from Internet applications to phone and increases satisfaction of mobile subscriber user experience.

This paper exploits characteristics of MMS, presented a framework, MMSEmail, for MMS-enabled email presentation. MMSEmail not only implements immediate email delivering by utilizing PUSH mechanism of MMS, but also supports user profile-based content adaptation and text presentation of Email attachments with special file types as. doc,. rtf and. pdf, thus provides an alternative means to present emails on mobile terminals.

The rest of this paper is structured as follows: Section 2 provides an overview of MMS. Section 3 presents the architecture and characteristics of our MMSEmail. Section 4 goes into more depth on content adaptation and section 5 concludes with a summary.

SECTION II.
Multimedia Messaging Service

A. Architecture of MM

MMS is developed in accordance with 3GPP standards (3GPP TS 23.140 [1]) and WAP Forum standards (WAP-205, 206 and 209 [2]– [4]). A reference of MMS architecture and a conclusion of its external interfaces are depicted in Fig. 1.

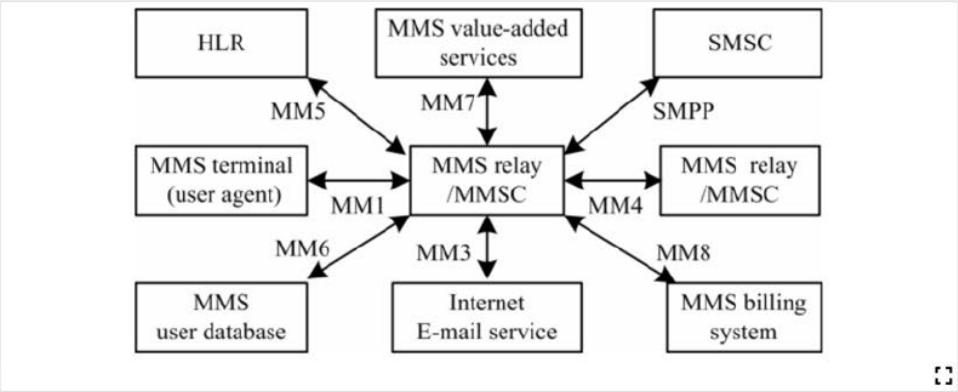


Figure 1. A reference of MMS architecture.

In MMS architecture, the core component is MMS Center (MMSC). The interface between MMSC and other external components can be concluded as follows:

- MM1: the interface between MMS user agent and
- MMSC. It is used for sending and retrieving multimedia messages (including PULL and PUSH) and for notifying message arrival or delivering report.
- MM2: the interface between MMS Relay and MMSC.

- MM3: the interface between MMSC and external servers (such as e-mail server).
- MM4: the interface between MMSC and other MMS relay servers.
- MM5: the interface between MMSC and HLR.
- MM6: the interface between MMSC and user DB.
- MM7: the interface between MMSC and value-added service (VAS) applications.
- MM8: the interface between MMSC and the billing systems.

B. Sending and Receiving an MM

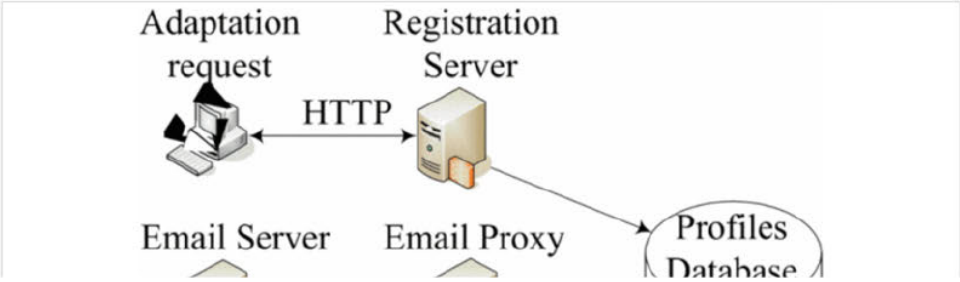
The following steps provide a general view of transaction flow for delivering a multimedia message (MM) between two mobile phones.

- MM sender invokes a WSP/HTTP POST request to MMSC with the message embedded as the content body.
- MMSC responds to the request, caches the received MM and then informs the receiver that an MM is available. The information conveyed shall include an URI that will be used to actually retrieve the message in a subsequent operation by MM receiver.
- MMS supports message fetch with "immediate retrieval" transaction or "delayed retrieval" transaction. MM receiver initiates the retrieval activity with the specified URI using a WSP/HTTP GET operation. Receiver client can convey its capabilities to MMSC.
- MMSC delivers the specified MM to the receiver.
- The receiver invokes a WSP/HTTP POST operation to confirm having received the MM.
- MMSC sends delivery report to originate sender.

SECTION III.
MMSEMAIL

A. Architecture of MMSEmail

MMSEmail is designed to deliver emails to mobile phone through MMS. It provided an external interface for accepting adaptation request through HTTP registration. The request contains the email address and its username and password, the destination phone number, the preference information and the expired time of request. During the term of valid registration, the registered user profile is stored into Profiles database. An Email proxy will check the database with regular intervals. If a request is activated, the email proxy acts as the email client, connect to the specified Email server and fetch emails, then pass them to the Content Adaptation Broker. The Broker adapts the submitted email according to rules in Profiles database, converts them to SMIL format and returns them to the Email proxy. The Email proxy then starts to send them each with an MMS to the destination phone. MMSEmail implemented an MMS sender with a GPRS modem and third-party MMS SDK. The generated MM can be sent as real MM and factually presented on the screen of the destination phone. The architecture of MMSEmail is shown in Fig. 2.



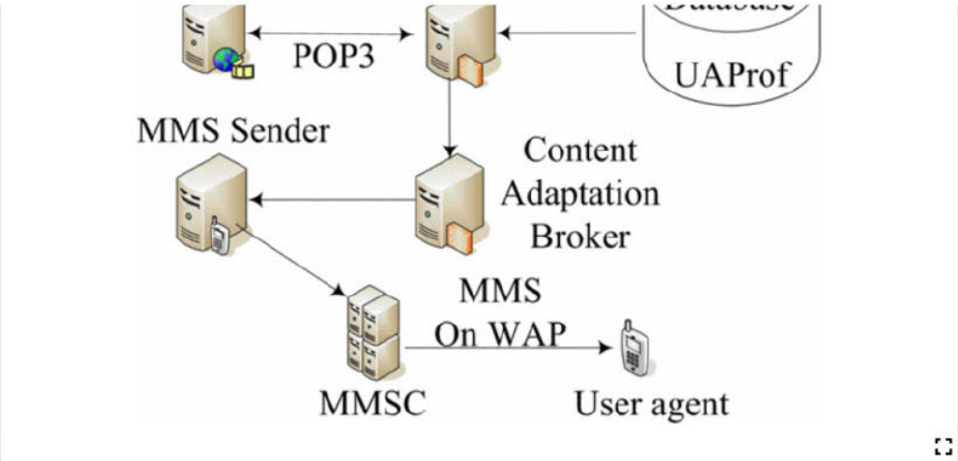


Figure 2. Architecture of MMSEmail.

B. Personalized Aadaptation Support

In order to extend MMSEmail's capability of supporting personalized adaptation, MMSEmail considers two ways to acquire CPI (Capability Preference information) of the receptor: by the specialized User-Agent parameter in registration profile or by parsing CC/PP[5] and UAProf [6] with free libraries such as HP's DELI (http://delicon.sourceforge.net/).

W3C's CC/PP (Composite Capability / Preference Profile) and WAP forum's UAProf are compatible standards. CC/PP defines a high-level structured framework for describing and transmitting information about the capabilities of Web clients and the display preferences of Web users using the Resource Description Framework (RDF). UAProf is a variant of CC/PP and have become the industry standard for describing and exchanging CPI of mobile terminals. The UAProf of a mobile terminal is often stored in a profile depository which is generally maintained by its manufacturer and its URL can be conveyed with some headers in request, such as x-wap-profile or Profile. The adapting proxy can retrieve its CPI by parsing the received XML document.

In first phase, we utilize the capability and preference information of the receiving terminal submitted by its user during registration.

C. Email Proxy

Most Internet-based email accounts use POP3 (Post Office Protocol v.3). POP3 allows an email client to collect the email on a remote server (POP server). Initially, the server host starts the POP3 service by listening on TCP port 110. When an email client wishes to make use of the service, it establishes a TCP connection with the server host. When the connection is established, the POP3 server sends a greeting. The client and POP3 server then exchange commands and responses (respectively) until the connection is closed or aborted [7].

Our POP3 proxy is an application level proxy for POP3 protocol. It establishes connection, trough remote servers, with POP3 clients. The proxy has multiple threads, each checks the email servers in its list in turns and in a time period interval. It reads the login ID, determines which server the account is located on, connects to the server, and logs in. Then, it fetches the new mails back and forwards them to content adaptation broker. After all email messages from an ID is retrieved and forwarded, the connection is closed. Flow control mechanism is considered to fine tune the server's performance and avoid overloading the POP3 proxy. A session is determined to be timeout if the proxy doesn't see any data received from remote email server within 30 seconds. The checking interval can be set from several minutes to several hours. The maximum number of active connections can be configured to limit the number of threads that can be simultaneously opened at a specific moment of time.

SECTION IV.
Content adaptation broker

Content adaptation is a process to convert the content unsupported by the receptor to the content the receptor

understands, while keeps the meaning of source content as far as possible. MMSEmail focuses on two categories of adaptation techniques: structure adaptation which reorganizes the series of object into a SMIL file (currently it had implemented a module to adapt an Email to a SMIL file) and media object adaptation which adapts the format and quality of multimedia objects (currently it had implemented modules of retrieving text from special type file of. doc,. pdf and. rtf).

A. SMIL Convertor

In accordance with "MMS Conformance Document" [8], Synchronized Multimedia Integration Language (SMIL) should be used as the presentation language for MM. Since mobile terminals may not allow us to take full advantage of the presentation capabilities offered by SMIL 2.0 or its simplest profile "SMIL Basic", [8] identifies a very limited subset of SMIL elements (MMS SMIL) for the first phase of MMS.

An MM consists of a "slide show", that is, a succession of one or several pages, each containing at most two regions: one for text and the other contains either an image or a video clip. A simple scheme of the organization of a MM is depicted in Fig. 3.

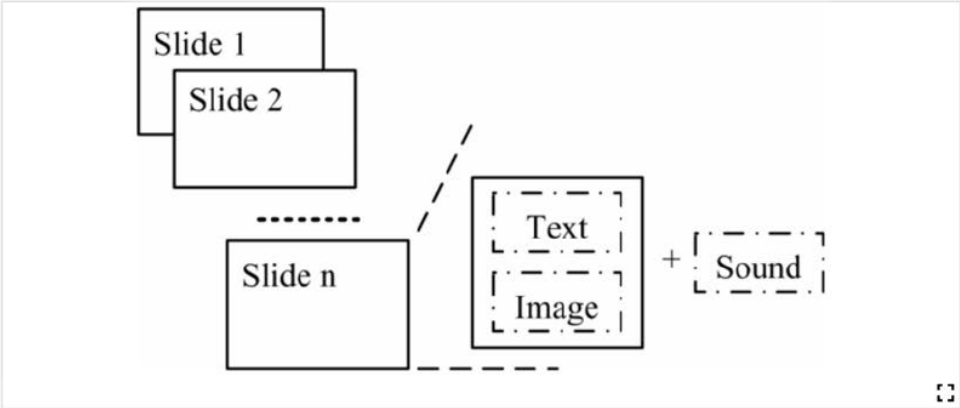
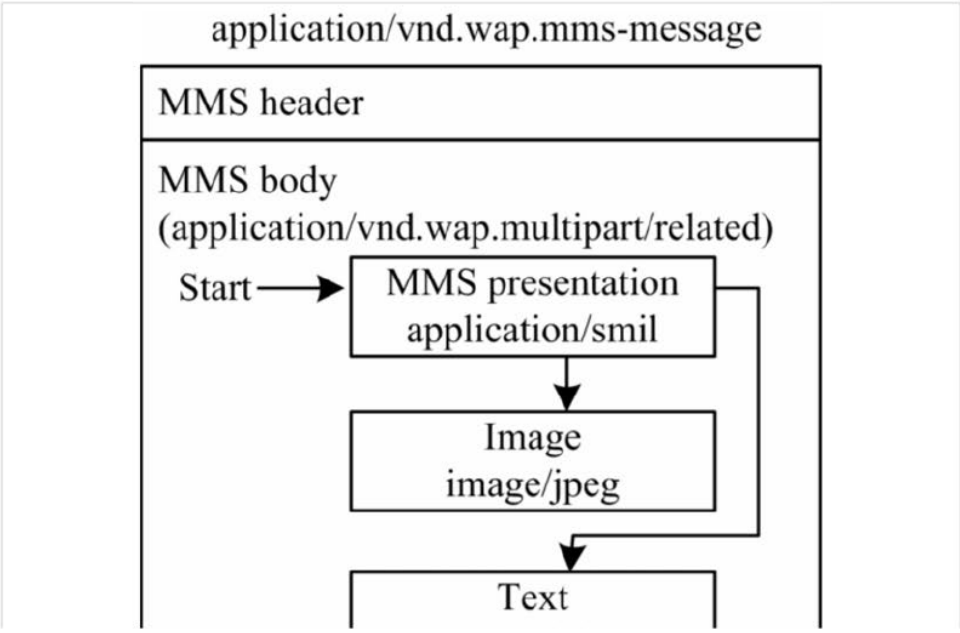


Figure 3. Structure of an MM.

MMSEmail only retrieves the sender, time, receiver and subject from the header of an Email. For decoded text of the body and attachments, MMSEmail fragments the extracted text object into blocks whose length is at most 30KB and parks them into the body part of MMS PDU (Fig. 4). Before factually sent to the destination phone, the newly generated MM can be tentatively presented on a desktop computer, e.g., with SMILSlidePlayer developed by MDS Technology Co. Ltd to verify the adaptation effects.



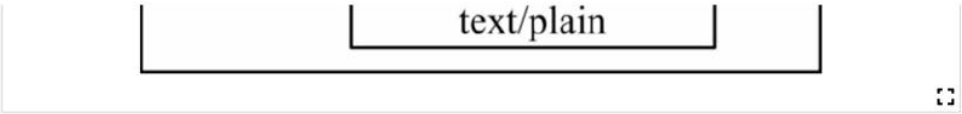


Figure 4. An example of MMS PDU.

B. Media Object Adapter

Some attachment rule is implemented to tell the proxy how to process email attachments. These rules include removing all attached files, removing attachments containing keywords, converting attachments to text, et al.

[8] defines the maximum set of requirements and guidelines for end-to-end interoperability of MMS. It specifies a suite of media types, formats and maximum size belonging to "Core MM Content Domain". There are some differences in media formats and size between 3GPP and 3GPP2 standards. For MM Content Class Text in 3GPP, the maximum length can be 30KB, the character set can be US-ASCII, UTF-8 and UTF-16. For MM Content Class Image Basic, the maximum length can be 30KB, the resolution of image can be 160*120. Still Image can be Baseline JPEG, Bitmap can be GIF87a, GIF89a and WBMP. For MM Content Class Image Rich, the maximum length can be 100KB, the maximum image resolution can be 640*480. For MM Content Class Video Basic, the video format can be H.263 and AMR. The maximum length of Video Rich can even be 300KB.

MMSEmail reserves interfaces for incorporating appropriative tools or APIs freely available on Internet to convert media types or size. The adapted objects are then embedded into a SMIL file. For multimedia playing, SMIL timing and synchronization elements can be taken into consideration, particularly <par>……</par> parallel time container.

C. Text Extractor

MMSEmail implements modules for automatically extracting text from email attachments with file types. html,. pdf,. doc and. rtf [9].

The structure of PDF file contains four parts: header, body, cross-reference table and trailer. The first line of a PDF file is a header identifying the version of the PDF specification to which the file conforms. The PDF document body contains a collection of objects such as fonts, graphics and pages. Cross-reference table is stored at the end of the PDF file and can be used to locate and directly access pages and other important objects within the file. The trailer contains the keyword startxref and the byte offset from the beginning of the file to the beginning of the xref keyword in the last cross-reference section, which enables PDF reading application can quickly find the cross-reference table and certain special objects. By locating the trailer, searching cross-reference table and finding objects within PDF file, MMSEmail repeatedly retrieves text-stream between "stream" and "endstream" sections and decodes them through calling ZLIB library API, all strings between "BT" and "ET" are extracted as text content of the PDF file.

The. doc file parser of MMSEmail fulfills the functions of format analyzing of. doc file header and FIB (File Information Block), recognizing the text-stream, extracting and transcoding the text. For. doc files containing Chinese characters, MMSEmail needs to convert Unicode to GBK code which is the default code of Windows platform.

RTF provides a format for text and graphics interchange that can be used with different OS. An RTF file consists of unformatted text, control words, control symbols and groups. The control words, control symbols (backslash '\'), and braces ({ }) constitute control information. The. rtf file parser evaluates and separates control information from plain text, acts on control information and collects text from the document. All other characters in the file are plain text. A standard RTF file can consist of only 7-bit ASCII characters, all characters above 0×80 must be in the escaped form, \'hh. So for. rtf file with Chinese characters, when MMSEmail encounters raw characters in the leading-byte range of the double-byte character, it regards the next character as the trailing byte of the double-byte character and combines the two characters into one double-byte character.

SECTION V.
Conclusion and future works

With the development of mobile communication, there arises the requirement of ubiquitous access to Internet Email service from small screen terminals such as mobile phones and PDAs. In view of the advantages of MMS, we

design a framework, MMSEmail, for adapting Email to MMS. MMSEmail is capable of: 1) decoding email attachments and converting. pdf,. doc and. rtf files to text; 2) encapsulating the meta-data retrieved from Email header and text converted from Email body and attachments into MMS SMIL; and 3) validating the presentation effect of the generated MM. Our method provides a new way for immediate Email delivery to mobile communication terminals. As a result of adopting industry standard interfaces, the architecture can be flexibly extended to other MMS-enabled applications.

In future, MMSEmail will implement adaptation algorithms for other media objects and synthesizes them with the extracted text into SMIL, so that the presentation effect of the adapted MMS comports with that of a normal PC-version Email clients.

ACKNOWLEDGMENT

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Damping control of small actuator for moving heads of VCRs

Publisher: IEEE Cite This PDF

K. Nakatsu ; Y. Furuishi ; Y. Kanagawa **All Authors**

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Abstract:
In order to realize a narrow track recording mechanism for VCRs, the concept of DTF (dynamic track following) system using a small actuator was developed. A major problem in the DTF system for high-density recording lies in the mechanical vibration characteristics of the small actuator which moves the head. A damping control system with a velocity feedback loop for realizing high-performance DTF system is described, and this velocity feedback system makes it possible to markedly suppress the first mode vibration of the small actuator.<>

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