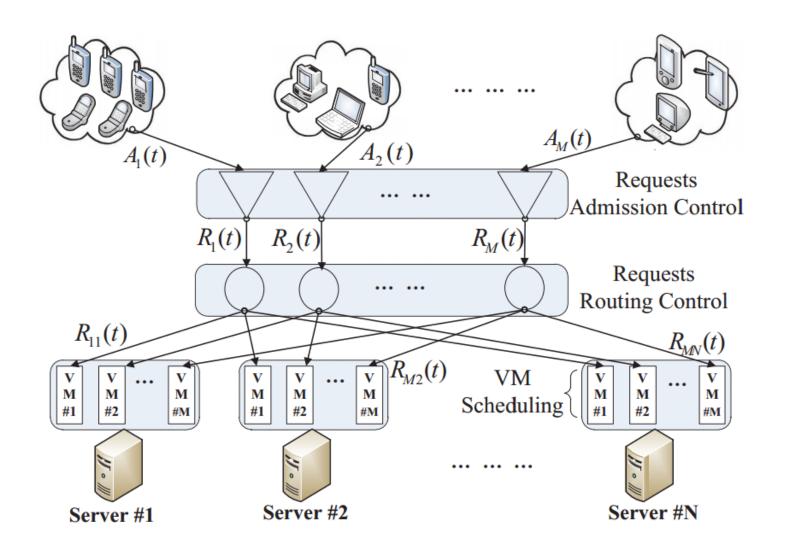
On Arbitrating the Power-Performance Tradeoff in SaaS Clouds

Presented by Xuanjia Qiu Feb. 1, 2013

Why I pick this paper

- To appear in INFOCOM 2013, as a full paper
- Simple model and rich results
- Relevance to my current work

On Arbitrating the Power-Performance Tradeoff in SaaS Clouds



Assumption

- One data center
- N homogeneous servers
- Each server is virtualized to M VMs to serve M types of heterogeneous application
- Applications have diverse request arrival rates and workload (but identical for requests from an application)
- CPU-bounded application only
- Cost -> Power consumption -> CPU load

- Time slot t=0,1,2,3,...
- $A_i(t)$ requests arrive at the data center (*i* is the type of application), i.i.d. over time slots. $A_i(t) <= A_i^{max}$

Control Decisions

- Admission Control: R_i(t), 0<=R_i(t)<=A_i(t)
- Routing Control: R_{ii}(t)
 - One request queue for each application(i.e., VM) in each server.
 - Constraint: $R_i(t) = \sum_{j=1}^N R_{ij}(t)$
- Scheduling of VMs (on or off)
 - $a_{ij}(t) = \begin{cases} 1, & \text{if the } i\text{-th VM on server } j \text{ is running,} \\ 0, & \text{if the } i\text{-th VM on server } j \text{ is idle.} \end{cases}$

$$Q_{ij}(t+1) = \max[Q_{ij}(t) - a_{ij}(t), 0] + d_i R_{ij}(t).$$

Modeling Cost

Power Cost

$$P(s) = \alpha s^v + (1 - \alpha)$$

- Normalize CPU load: $s_j(t) = \frac{\sum_{i=1}^M a_{ij}(t)}{M}$
- Power Cost: Price · PUE · $\sum_{j=1}^{N} p_j$
 - (PUE: Power Usage Effectiveness)
- Revenue of throughput $g(r_i) = \log(1 + d_i r_i)$
- Aggregation: $\max_{i \in \mathcal{A}} \sum_{j \in \mathcal{S}} p_j$ s.t. $0 \le r_i \le \lambda_i, r_i \le N/d_i, \quad \forall i \in \mathcal{A},$

Lyapunov Optimization

Original problem

$$\max \sum_{i \in \mathcal{A}} g(r_i) - \beta \sum_{j \in \mathcal{S}} p_j$$
s.t.
$$0 \le r_i \le \lambda_i, r_i \le N/d_i, \quad \forall i \in \mathcal{A},$$

After transformation

$$\max \sum_{i \in \mathcal{A}} g(\gamma_i) - \beta \sum_{j \in \mathcal{S}} p_j$$
(6)
s.t. $\gamma_i \le r_i, \quad \forall i \in \mathcal{A}$ (7)
 $0 \le r_i \le \lambda_i, \quad \forall i \in \mathcal{A}$ (8)
 $r_i \le N/d_i, \quad \forall i \in \mathcal{A}$. (9)

$$H_i(t+1) = \max[H_i(t) - R_i(t), 0] + \gamma_i(t),$$

$$0 \le \gamma_i(t) \le A_i^{\max}.$$

Lyapunov function

$$L(\boldsymbol{\Theta}(t)) = \frac{1}{2} \Big[\sum_{i \in \mathcal{A}} d_i^2 H_i^2(t) + \sum_{i \in \mathcal{A}} \sum_{j \in \mathcal{S}} Q_{ij}^2(t) \Big].$$

Drift-minus-profit

$$\Delta(\mathbf{\Theta}(t)) - V\mathbb{E}\Big\{\sum_{i \in \mathcal{A}} g(\gamma_i(t)) - \beta \sum_{j \in \mathcal{S}} P_j(t) |\mathbf{\Theta}(t)\Big\}.$$

Minimizing upper bound

$$\Delta(\Theta(t)) - V\mathbb{E}\Big\{\sum_{i\in\mathcal{A}}g(\gamma_i(t)) - \beta\sum_{j\in\mathcal{S}}P_j(t)|\Theta(t)\Big\} \leq B_1 \qquad \text{Auxiliary Variable Selection} \\ -\sum_{i\in\mathcal{A}}\mathbb{E}\{Vg(\gamma_i(t)) - d_i^2H_i(t)\gamma_i(t)|\Theta(t)\} \text{ (15)} \\ -\sum_{i\in\mathcal{A}}\mathbb{E}\Big\{d_i^2H_i(t)R_i(t) - \sum_{j\in\mathcal{S}}d_iR_{ij}(t)Q_{ij}(t)|\Theta(t)\Big\} \text{ (16)} \qquad \text{Request Admission Control and Routing} \\ -\sum_{j\in\mathcal{S}}\mathbb{E}\Big\{\sum_{i\in\mathcal{A}}Q_{ij}(t)a_{ij}(t) - V\beta P_j(t)|\Theta(t)\Big\}. \text{ (17)} \qquad \text{VM Scheduling}$$

Auxiliary Variable Selection

$$\max_{\gamma_i(t)} V \log(1 + d_i \gamma_i(t)) - d_i^2 H_i(t) \gamma_i(t)$$
s.t.
$$0 \le \gamma_i(t) \le A_i^{\max}, \forall i \in \mathcal{A}.$$

Differentiating the objective function,

$$\gamma_{i}(t) = \begin{cases} 0, & H_{i}(t) > \frac{V}{d_{i}} \\ \frac{V}{d_{i}^{2}H_{i}(t)} - \frac{1}{d_{i}}, & \frac{V}{d_{i}^{2}A_{i}^{\max} + d_{i}} \leq H_{i}(t) \leq \frac{V}{d_{i}} \\ A_{i}^{\max}, & H_{i}(t) < \frac{V}{d_{i}^{2}A_{i}^{\max} + d_{i}} \end{cases}$$
(19)

Request Admission Control and Routing

$$\max_{R_{i}(t),R_{ij}(t)} d_{i}^{2}H_{i}(t)R_{i}(t) - d_{i}\sum_{j\in\mathcal{S}}R_{ij}(t)Q_{ij}(t) \quad (20)$$
s.t.
$$0 \leq R_{i}(t) \leq A_{i}(t), \forall i \in \mathcal{A},$$

$$R_{i}(t) = \sum_{j\in\mathcal{S}}R_{ij}(t).$$

 Making Routing first, by assuming R_i(t) is known

$$\min_{R_{ij}(t)} d_i \sum_{j \in \mathcal{S}} R_{ij}(t) Q_{ij}(t)
\text{s.t.} \sum_{j \in \mathcal{S}} R_{ij}(t) = R_i(t), \forall i \in \mathcal{A}.$$
(21)

$$\min_{R_{ij}(t)} d_i \sum_{j \in \mathcal{S}} R_{ij}(t) Q_{ij}(t)$$
s.t.
$$\sum_{j \in \mathcal{S}} R_{ij}(t) = R_i(t), \forall i \in \mathcal{A}.$$
(21)

- Solution
 - Dispatch as many admitted requests as possible to the VM with shortest backlogged queue:

$$R_{ij}(t) = \begin{cases} R_i(t), & j = j_i^*, \\ 0, & \text{else,} \end{cases}$$

 Complexity reduced by the solution by "Power of the two choices", but compromising the rigor of optimality analysis

Combine the results:

$$\max_{R_{i}(t),R_{ij}(t)} d_{i}^{2}H_{i}(t)R_{i}(t) - d_{i}\sum_{j\in\mathcal{S}}R_{ij}(t)Q_{ij}(t) \quad (20)$$
s.t.
$$0 \leq R_{i}(t) \leq A_{i}(t), \forall i \in \mathcal{A},$$

$$R_{i}(t) = \sum_{j\in\mathcal{S}}R_{ij}(t).$$

$$R_{ij}(t) = \begin{cases} R_i(t), & j = j_i^*, \\ 0, & \text{else,} \end{cases}$$

Get

$$\max_{R_i(t)} d_i^2 H_i(t) R_i(t) - d_i R_i(t) Q_{ij_i^*}(t)$$
s.t.
$$0 \le R_i(t) \le A_i(t), \forall i \in \mathcal{A}.$$
(23)

VM Scheduling

$$\max_{a_{ij}(t)} \sum_{i \in \mathcal{A}} Q_{ij}(t) a_{ij}(t) - V \beta P_j(t)$$
s.t.
$$a_{ij}(t) \in \{0, 1\}, \forall i \in \mathcal{A}, \forall j \in \mathcal{S},$$

$$P_j(t) = \alpha(\frac{\sum_{i=1}^{M} a_{ij}(t)}{M})^v + (1 - \alpha)$$

 Greedy algorithm: search from VM with most backlogged queue to the least, until the growth in the sum of backlogs falls below the growth of the power consumption for a certain VM

Analytical Results

Theorem 1: For arbitrary arrival rates of application requests $(\lambda_1(t), \lambda_2(t), ..., \lambda_M(t))$ (possibly exceeding the processing capacity of a datacenter), a datacenter using the **OCA** algorithm with any $V \ge 0$ (the stability-profit tradeoff parameter defined in Sec. III-A1) can guarantee that all the actual and virtual queues are strongly stable over time slots:

$$H_i(t) \le \frac{V}{d_i} + A_i^{\max}, \forall i \in \mathcal{A},$$
 (26)

$$Q_{ij}(t) \le V + 2d_i A_i^{\text{max}}, \forall i \in \mathcal{A}, \forall j \in \mathcal{S}.$$
 (27)

Meanwhile, the gap between its achieved time averaged profit and the optimal profit ξ^* is within B_1/V :

$$\liminf_{t \to \infty} \left\{ \sum_{i \in \mathcal{A}} g(r_i) - \beta \sum_{j \in \mathcal{S}} p_j \right\} \ge \xi^* - \frac{B_1}{V}, \tag{28}$$

where $\xi^* = \sum_{i=1}^M g(r_i^*) - \beta \sum_{j=1}^N p_j^*$, r_i^* and p_j^* are the optimal solution to **Problem** (5), and B_1 is a finite constant parameter defined in Lemma 1.

Evaluation

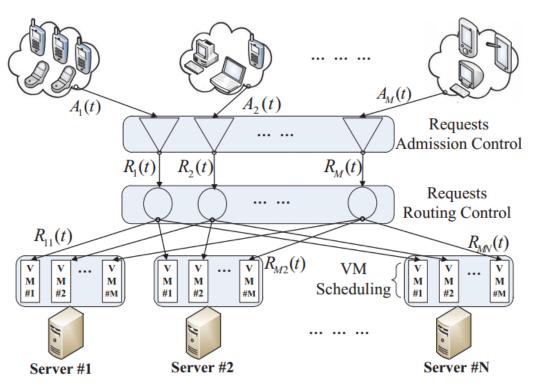
- Assumption and input
 - 100 servers, 10 VMs on each server
 (corresponding 10 heterogeneous applications)
 - Number of newly arrived requests in each time slot is assumed to be uniformly and randomly distributed within [0, A_i^{max}]

TABLE II: Request Arrival Rates and Sizes of Different Applications.

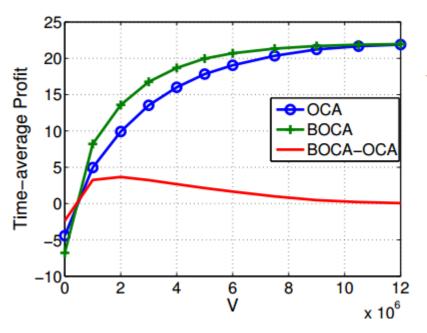
App i	1	2	3	4	5	6	7	8	9	10
$\lambda_i(\times 10^3)$	2.5	2	3.5	2	3	2	2.75	2.4	2.6	2.8
$d_i(\times 10^{-2})$	2	3	2	4	3	5	4	5	5	5
$d_i\lambda_i(\times 10)$	5	6	7	8	9	10	11	12	13	14

Buffer or not buffer?

 Store the newly admitted requests in a buffer before they are routed to VMs



Buffer or not buffer?



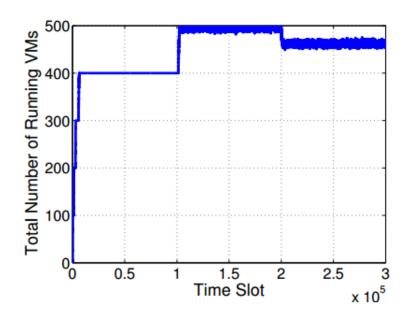
$$L(\Theta(t)) = \frac{1}{2} \Big[\sum_{i=1}^{M} d_i^2 H_i^2(t) + \sum_{i=1}^{M} d_i^2 L_i^2(t) + \sum_{i=1}^{M} \sum_{j=1}^{N} Q_{ij}^2(t) \Big]$$

$$\liminf_{t \to \infty} \left\{ \sum_{i=1}^{M} g(r_i) - \beta \sum_{j=1}^{N} p_j \right\} \ge \xi^* - \frac{B_2}{V}$$

- $B_2 > B_1$
- Buffering is no better than no-buffering.
- Reasoning: too many queues, reducing the weight on performance

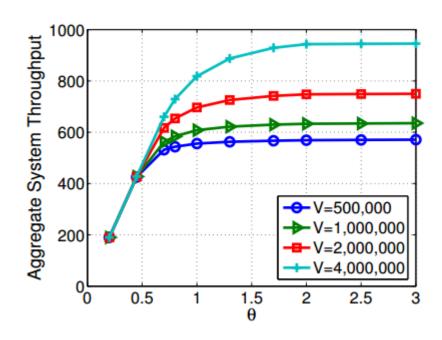
Selected Evaluation Results

- In response to bursty request arrivals
 - Vary the mean request arrival rates to be 0.5, 1, and 1.5 times of the original



Selected Evaluation Results

Effectiveness of admission control



Selected Points that we can learn from

Model

 Workload of requests are normalized according to the VM processing capacity in one time slot, and <1

Solution

- Dig the optimality structure of sub-problem first
- Use greedy algorithm to solve non-linear, nondifferentiatable optimization problem

Evaluation

 Compare different queueing models (buffer against no-buffer)

Q&A