Energy Cost Minimization with Risk Rate Constraint for Internet Data Center in Deregulated Electricity Markets

Zhongjin Li[1], Jidong Ge[1], Chuanyi Li[1], Hongji Yang[2], Haiyang Hu[3] and Bin Luo[1]
[1]State Key Laboratory for Novel Software Technology, Software Institute, Nanjing University, Nanjing, China
[2]Centre for Creative Computing (CCC), Bath Spa University, England, U.K.
[3]School of Computer, Hangzhou Dianzi University, Hangzhou, China

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Abstract: With the large-scale development of internet data center (IDC), the energy cost is increasing significantly and has attracted a great deal of attention. Moreover, existing scheduling optimization methods for cloud computing applications disregard the security services. In this paper, we propose a long-term energy cost minimization (ECM) algorithm with risk rate constraint for an internet data center in deregulated electricity markets. First, we formulate the stochastic optimization problem taking the temporal diversity of electricity price and risk rate constraint into account. Then, an operation algorithm is designed to solve the problem by Lyapunov optimization framework, which offers provable energy cost and delay guarantees. Extensive evaluation experiments based on the real-life electricity price demonstrate the effectiveness of proposed algorithm.

1 INTRODUCTION

Cloud computing supported by the infrastructure called internet data center (IDC) is a large-scale distributed computing platform to meet the skyrocketing demand of online applications and services. Recently, a cloud and non-cloud storage is deployed for biomedical scientists to conduct the performance comparisons, which show that the cloud system outperforms the non-cloud system on execution time, consistency, efficiency improvement (Chang and Wills, 2015). As an IDC typically comprises thousands of servers, energy consumption or energy cost is one of the critical problems.

Recently, IDC operators have developed many scheduling strategies to minimize the energy cost by exploiting the electricity price dynamics across geographically distributed regions (Rao et al., 2010, 2011). In the real life, electricity price manifests not only spatial diversity but also temporal diversity. For instance, in North America, due to the different power generation profiles, many electricity markets have been deregulated in which the electricity prices are not constant but vary on an hourly or 15-min basis (Shao et al., 2014).

Besides energy consumption and energy cost, security is another critical concern for IDC on a wide range of applications. Nowadays, several recent works tackle the security problem on clusters (Xie and Qin, 2006), grid computing (Song et al., 2006), heterogeneous distributed system (Xie and Qin, 2007; Tang et al., 2011) and cloud computing (Zeng et al., 2015; Chang, 2014, 2015; Chang et al., 2015). Unfortunately, since distributed computing is built to execute a broad spectrum of unverified user-implemented applications by a vast number of users, both applications and users can be sources of security threats to computing environments (Yurcik et al., 2004). However, many existing cloud computing environments have not employed any security mechanism to counter the security threats (Ali et al., 2015).

In this paper, we propose an energy cost minimization (ECM) algorithm for an IDC in an environment where the electricity price exhibits temporal diversity and the workload is dynamic. The security services are incorporated into the tasks arrived, and the average risk rate constraint of all executed tasks must be satisfied. The energy cost minimization framework is shown in Figure 1. First, all tasks arrived in IDC are enqueued into a FIFO queue. Then, the workload shaping method is employed to measure the workload based on the task itself and security services. Finally, we apply the

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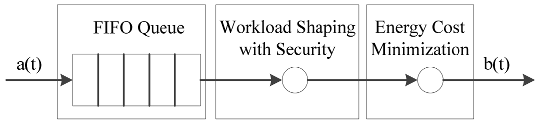


Figure 1: The energy cost minimization framework.

ECM algorithm which based on the Lyapunov optimization framework to solve the problem. In ECM algorithm, our purpose is to minimize energy cost by deciding: 1) how many tasks should be processed in each time slot; 2) which security levels should be selected for these tasks; and 3) how many resources should be provided by IDC.

The main contributions of this paper can be summarized as follows:

- We present an energy cost minimization algorithm for IDC while incorporating the security services of application. Furthermore, the time average risk rate constraint for the queue system is satisfied.
- We exploit the temporal diversity of electricity price to minimize the energy cost in deregulated electricity markets by scheduling workload in a temporal context.
- We design a polynomial time complexity algorithm to solve the problem based on Lyapunov optimization technique, which can facilitate energy cost versus delay trade-off for internet data center.

The rest of this paper is organized as follows. Section 2 summarizes the related work. Section 3 describes some system models and problem formulation. Section 4 introduces the algorithm design and performance analysis. The performance evaluation approaches and results are conducted in Section 5. Section 6 concludes this paper and envisages our future work.

2 RELATED WORK

Security is one of the critical problems in distributed computing environment. However, only few groups of researchers investigate the security-driven scheduling policy from different points of view. Song et al. (2006) develop three risk-resilient strategies and a genetic algorithm to provide security assurance in grid job scheduling. Xie and Qin (2006, 2007) study a family of dynamic security-aware scheduling algorithms for homogeneous clusters and heterogeneous distributed systems. Tang et al. (2011) design a security-driven scheduling architecture that can dynamically measure the trust level of each node. Zeng et al. (2015) introduce a security-aware and budget-aware workflow scheduling strategy (SABA), to provide customers with shorter makespan and security services. Chang (2014) uses business intelligence as a service in the cloud (BIaaS) to permit organizations to break the constraints of the desktop. Then, a revised and improved technique, organizational sustainability modelling (OSM), is proposed to consider the application of capital asset price modelling (Chang et al., 2015).

For IDC service providers, high energy consumption means enormous electricity cost budgets. Qureshi et al. (2009) investigate the feature of electricity price in deregulated electricity markets, i.e., electricity prices exhibit both temporal and spatial variations. Rao et al. (2010) study the problem of minimizing the total electricity cost under multiple electricity markets environment. Shao et al. (2014) take the transmission delay into their design consideration and formulate a mixed-integer nonlinear programming (MINLP) problem with coupled constraint. Luo et al. (2014) study an important energy management problem and propose a novel two-stage design and the eco-IDC (energy cost optimization-IDC) algorithm to exploit the temporal diversity of electricity price. Yu et al. (2014) propose a risk-constrained decision framework to achieve the optimal tradeoff between expected energy cost and operation risk.

A number of recent works introduce new aspects in better usage of power in data centers. Urgaonkar et al. (2011) investigate cost reduction opportunities that arise by the use of uninterrupted power supply (UPS) units as energy storage devices. Yu et al. (2015) minimize energy cost by scheduling workload and battery jointly, which can fully exploit the temporal diversity of electricity price. Guo et al. (2013) develop an online algorithm to minimize energy cost with batteries, which can utilize the temporal diversity of electricity price. Liu et al. (2012) consider server management together with cooling and usage of renewable energy. Then, they investigate the problem of minimizing the long-term energy cost with the uncertainties in electricity price, workload, renewable energy generation, and power outage state (Liu et al., 2015).

However, both energy cost and security are critical for IDC. Different from the above works, our research investigates the energy cost minimization with risk rate constraint for internet data center in deregulated electricity markets.

3 MODELS AND PROBLEM FORMULATION

In this section, we model an IDC system and formulate a long-term energy cost optimization problem. For ease of understanding, we summarize the major notations and their meanings used in this paper in Table 1.

3.1 IDC Resource Capacity

We consider a discrete-time system evolving over a sequence of equal-length time slots. The IDC resources are quantified in unit of *basic resource unit* (Luo et al., 2014). A basic resource unit may include a number of microprocessor cores, an amount of memory and so on. Thus, an IDC resource capacity is in unit of *basic resource unit· time slot*. When an IDC receiving service requests, it needs to allocate a certain amount of resource $R(t)$ for them according to the workload requirement in time slot t. We also assume that there exists $R_{\min}$ and $R_{\max}$ such that $R_{\min} \le R(t) \le R_{\max}$ and the scaling time of which can be negligible related to unit time slot.

Generally, an IDC task can be generally classified as delay-sensitive, or delay-tolerant (Luo et al., 2014). In this paper, we focus on the tasks in delay-tolerant requests which include compute-intensive or data-intensive jobs, such as scientific computing and data intensive applications. For example, it is indicated that Google often has a large number of " long duration" jobs running on back-end servers (Mishra et al., 2010).

3.2 Security Model

Since snooping, alteration, and spoofing are three common attacks in cloud environments, we consider three security services (i.e., authentication service, integrity service and confidentiality service) to guard against the common threats (Xie and Qin, 2006).

We consider that each task may require three security services with various security levels. For example, sl_i is the set of security levels of task t_i provided by IDC operator, which can be specified as a K-vector $sl_i = (sl_i^1, sl_i^2, ..., sl_i^k, ...sl_i^K)$, where sl_i^k represents the security level of k th security service and $K = 3$. An example of security levels of cryptographic algorithm for confidentiality is shown in Table 2. For the sake of simplicity, we use letters a, g and c to represent the authentication, integrity and confidentiality respectively.

Table 1: Notations.

Symbol	Definition
$R(t)$	Resource capacity in time slot t ;
sl_i	The set of security levels of task t_i ;
sl_i^k	Security level of kth security service;
SL^k	The set of security service;
$a(t)$	The number of tasks arriving at IDC;
$b(t)$	The number of tasks is processed ;
SW_i^k	Security workload;
SW_i	Total security workload of task t_i ;
EW_i	Execution workload of task t_i ;
W_i	Total workload of task t_i ;
$r_i(sl_i^k)$	Risk rate of the k th security service;
$r_i(t)$	The risk rate of task t_i in time slot t ;
$u(t)$	Average risk rate of tasks;
λ	Average task arrival rate;
$C(t)$	Energy cost of IDC in time slot t ;
$p(t)$	Electricity price in time slot t ;
$Q(t)$	Queue backlog in time slot t ;
$Z(t)$	Virtual queue;
$L(\mathbf{\Theta}(t))$	Lyapunov function;
$\Delta(\mathbf{\Theta}(t))$	Conditional Lyapunov drift.

Table 2: Cryptographic Algorithm for Confidentiality.

Cryptographic Algorithms	sl^c : Security Level	Processing Rate: KB/ms
SEAL	0.08	168.75
RC4	0.14	96.43
Blowfish	0.36	37.50
Knufu/Khafre	0.40	33.75
RC5	0.46	29.35
Rijndael	0.64	21.09
DES	0.90	15.00
IDEA	1.00	13.50

3.3 Task Arrival and Workload Shaping

We consider the IDC which has one service queue for delay-tolerant tasks and denote the corresponding queue as $Q(t)$ which is assumed to operate in a discrete time-slot manner, i.e., $t = 0,1,2,...$, where $Q(t)$ represents the queue backlog. In every time slot t , we denote the amount of newly arrived tasks as $a(t)$. The variable $a(t)$ is the stochastic arrival with $E\{a(t)\} = \lambda$, and it is assumed to be non-negative. This process is assumed to be independent of the current amount of unfinished tasks in the queue system and has finite second moment. Moreover, suppose that there exists a maximum A_{max} such that $a(t) \le A_{max}$ for all time slot t. All arriving tasks, which are computation-intensive, are queued into the FIFO queue that is shown in Figure 1, and CPU resource is the bottleneck resource. For simplicity, we assume that all tasks arrive at the end of each time slot.

For each task arriving at IDC, it needs security services to ensure its successful execution. The security service also introduces some time overhead to the computing systems. The definitions of time overhead of kth security service can be found in detail in (Xie and Qin, 2006, 2008). Different from the time overhead, each security service is inverted into the security workload which is denoted by:

$$SW_i^k = F^k(sl_i^k, d_i^k),\ k \in \{g, c\} \tag{1}$$

where symbol SW_i^k represents the security workload (in *basic resource unit*) of kth security service and d_i^k is the data of task t_i to be protected. The function $F^k(\cdot,\cdot)$ can be induced from (Xie and Qin, 2006), and we can easily get the following property:

Property 1. *The function* $F^k(\cdot,\cdot)(k \in \{g, c\})$ *should satisfy the following conditions:*

- If $sl_i^k = 0$ or $d_i^k = 0$, then $F^k(sl_i^k, 0) = 0$ or $F^k(0, d_i^k) = 0$;
- If $sl_1^k = sl_2^k$ and $d_1^k < d_2^k$, then $F^k(sl_1^k, d_1^k) < F^k(sl_2^k, d_2^k)$;
- If $d_1^k = d_2^k$ and $sl_1^k < sl_2^k$, then $F^k(sl_1^k, d_1^k) < F^k(sl_2^k, d_2^k)$;

The three conditions reflect the security service workload associated with security levels and the protected data. However, the security overhead of each authentication service is a constant value which only depends on the service type. Hence, the security workload of authentication service is computed by Eq. (2).

$$SW_i^k = F^k(sl_i^k),\ k \in \{a\} \tag{2}$$

We can also have the same property that $F^a(0) = 0$ and $F^a(sl_1^a) < F^a(sl_2^a)$ when $sl_1^a < sl_2^a$. Then, the total security workload of task t_i is represented by Eq. (3).

$$SW_i = \sum_{k \in \{a,g,c\}} SW_i^k \tag{3}$$

Finally, the workload of task t_i is denoted as follows:

$$W_i = EW_i + SW_i \tag{4}$$

where EW_i is the execution workload of task t_i. So, different from the existing work, the workload of a task includes two components.

3.4 Time-average Risk Rate

In this risk rate model, we derive the risk probability to quantitatively analyze the risk rate for a task t_i with different security levels. We assume that the risk rate is a function of security levels and the distribution of the risk for any fixed time interval follows a *Poisson* probability distribution. The risk rate model is used for illustration purpose only. Thus, the task's risk rate of the kth security service can be presented by an exponential distribution as follows (Xie and Qin, 2007; Tang et al., 2011):

$$r_i(sl_i^k) = 1 - \exp(-\lambda^k (1 - sl_i^k)), k \in \{a, g, c\} \tag{5}$$

In IDC, the risk coefficient λ^k is different from one to another. The negative exponent indicates that failure probability grows with the difference $1 - sl_i^k$, where we assume that the maximum security level of each security service is 1 (e.g. see Table 2). The risk rate of task t_i in time slot t can be obtained below by considering all the security services. Consequently, we have the following Eq. (6).

$$r_i(t) = 1 - \prod_{k \in \{a,g,c\}} (1 - r_i(sl_i^k)) \tag{6}$$

Let $b(t)$ represent the amount of tasks processed by IDC in time slot t, and $B_{max} \ge b(t), \forall t$ denotes the maximum number of tasks that can be served in a time slot. As the risk rate of each task is only related to the security levels, we assume that all tasks served in time slot t have the same security services, and hence the same of risk rate. Thus, we have

$$r_i(t) = r(t),\ i \in \{1, 2, ..., b(t)\} \tag{7}$$

This is the fairness for these tasks served in the same time slot t. Then, we define the average risk rate $\bar{u}$ of the IDC as follows:

$$\bar{u} = \lim_{t \to \infty} \frac{1}{\sum_{\tau=0}^{t-1} b(\tau)} \sum_{\tau=0}^{t-1} b(\tau) \cdot r(\tau) \tag{8}$$

where $\sum_{\tau=0}^{t-1} b(\tau)$ and $\sum_{\tau=0}^{t-1} b(\tau)\cdot r(\tau)$ are the total number of tasks and risk rates respectively. Nevertheless, when $t \to \infty$, the time-average arrival rate is equal to the time-average service rate, which is represented by Eq. (9).

$$\overline{b} = \lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} b(\tau) = \overline{a} = \lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} a(\tau) \tag{9}$$

We can also know that $E\{a(t)\} = \overline{a} = \lambda$. Then, the Eq. (8) can be rewritten as follows.

$$\overline{u} = \lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \frac{1}{\lambda} \cdot b(\tau) \cdot r(\tau) \tag{10}$$

Denote the average risk rate of tasks in time slot t as $u(t) = 1/\lambda \cdot b(t) \cdot r(t)$, and then $\overline{u}$ represents the time-average risk rate of $u(t)$.

3.5 Energy Cost Model

At time slot t, IDC operator provides $R(t)$ resource capacity for the current queued tasks according to the tasks workloads. The power requirement of resource capacity is denoted as $P(R(t))$. Symbol $P(\cdot)$ is the power function associated with resource capacity. We assume that the power function is known to IDC, and there exists a maximum value P_{max} such that $P(R(t)) \le P_{max}$ for all time slot t. Such power consumption will in turn incur some monetary cost for the data center of the form "power × price". To also model the fact that each IDC may face different electricity prices at time slot t in deregulated electricity markets, we denote it as $p(t)$. We assume that $p(t)$ is independent in every time slot t and takes a value in the finite state space. Then, the energy cost $C(t)$ of IDC in time slot t is computed by Eq. (11).

$$C(t) = P(R(t)) \cdot p(t) \tag{11}$$

We define p_{max} as the maximum electricity price that the IDC can experience. It is easy to see that if we have $C_{max} = P_{max} \cdot p_{max}$, then $C(t) \le C_{max}$ for all t.

3.6 Problem Formulation

In this paper, we are interested in minimizing the time-average expected energy cost which is represented as follows.

$$\overline{C} = \limsup_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} E\{C(\tau)\} \tag{12}$$

The electricity price $p(t)$ is changing in each time slot. If the IDC processes all the tasks in the queue $Q(t)$ in spite of the price, it will incur high energy cost but low service delay. On the contrary, if the IDC serve the tasks only when the electricity price is low, then the queue backlog $Q(t)$ will increase rapidly, consequently leading to large unacceptable delay. Hence, there is a *cost-delay tradeoff* in conducting the tasks execution. To balance such a tradeoff, we require the queue to be stable in the time average sense, i.e.,

$$\overline{Q} = \limsup_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} E\{Q(\tau)\} < \infty \tag{13}$$

where $Q(t)$ represents the time-average queue backlog, and the queueing dynamics can be characterized by Eq. (14).

$$Q(t+1) = max[Q(t) - b(t), 0] + a(t) \tag{14}$$

Condition (14) implies that all tasks arriving at the queue in IDC will be processed in bounded time. A larger value $\overline{Q}$ means a longer delay for tasks.

In order to ensure the security of all tasks, the time-average risk rate must subject to risk rate constraint, that is $\overline{u} \le u^{av}$, where u^{av} represents a pre-specified average risk rate constraint. In each time slot t, the IDC operator makes an online decision to minimize the energy cost under queue stability and time-average risk rate constraint.

$$\text{Minimize:} \quad \overline{C} = \limsup_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} E\{C(\tau)\} \tag{15a}$$

$$\text{Subject to:} \quad \overline{Q} < \infty \tag{15b}$$

$$\overline{u} \le u^{av} \tag{15c}$$

$$\sum_{i=1}^{b(t)} W_i \le R(t),\ R(t) \in [R_{min}, R_{max}] \tag{15d}$$

$$sl_i^k \in SL^k,\ k \in \{a, g, c\} \tag{15e}$$

$$b(t) \in \{0, 1, 2, ..., n(t)\} \tag{15f}$$

Inequality (15d) means that the resource capacity of IDC in time slot t should be equal or more than the task workload needed to be processed. For Eq. (15e), there are only limited levels for each security service. Let $n(t)$ represent the number of tasks of queue $Q(t)$ in time slot t, which is the maximum number of tasks that can be serviced by IDC. Therefore, parameter $b(t)$ has $(n(t)+1)$ choices for the FIFO queue system in time slot t.

Security services are used to prevent the tasks from tampering maliciously and accessing illegally. However, if users apply better security services for tasks, it will incur longer processing time, which will also result in more cost and larger delay. Hence, users can select proper risk rate constraint for all the tasks execution.

4 ALGORITHM DESIGN AND PERFORMANCE ANALYSIS

In this section, we design an ECM algorithm along with queue stability and average risk rate constraint based on the Lyapunov optimization framework (Georgiadis et al., 2006). This framework allows us to include energy cost into the *Lyapunov drift analysis*, a well-known technique for designing stable control algorithms. We now highlight the key steps in deriving ECM and then characterize its performance.

4.1 Algorithm Design

To ensure that the constraint Eq. (15c) is satisfied, we use a *virtual queue* $Z(t)$ with update equation as follows:

$$Z(t+1) = max\{Z(t) + u(t) - u^{av}, 0\} \tag{16}$$

Specifically, from Eq. (16) it is clear that

$$\begin{aligned} Z(t+1) &= max\{Z(t) + u(t) - u^{av}, 0\} \\ &\geq Z(t) + u(t) - u^{av} \end{aligned} \tag{17}$$

and hence

$$\frac{Z(t) - Z(0)}{t} + u^{av} \geq \frac{1}{t}\sum_{\tau=0}^{t-1} u(\tau) \tag{18}$$

Taking expectations of both sides and using $Z(0) = 0$ yields

$$\frac{E\{Z(t)\}}{t} + u^{av} \geq \overline{u} \tag{19}$$

It follows from Eq. (19) that if $E(Z(t))/t \to 0$, then $\overline{u} \leq u^{av}$. Stabilizing this virtual queue ensures that the time-average value of $u(t)$ is less than or equal to the time average risk rate constraint, which ensures Eq. (15c) (Neely, 2010).

Next, we first define the Lyapunov function, $L(\mathbf{\Theta}(t))$, which represent a scalar metric of queue backlog for reflecting delays of tasks, as follows:

$$L(\mathbf{\Theta}(t)) = \frac{1}{2}\Theta(t)^2 = \frac{1}{2}[Q(t)^2 + Z(t)^2] \tag{20}$$

where $\mathbf{\Theta}(t)$ is defined as $\mathbf{\Theta}(t) = [Q(t), Z(t)]$ which can evolve over slot $t \in \{0,1,2,...\}$, and $L(\mathbf{\Theta}(t)) \geq 0, \forall t$. To keep the system stable by persistently pushing the Lyapunov function towards a lower congestion state, we introduce the Lyapunov drift $\Delta(\mathbf{\Theta}(t))$ as follows:

$$\Delta(\mathbf{\Theta}(t)) = E\{L(\mathbf{\Theta}(t+1)) - L(\mathbf{\Theta}(t)) \mid \mathbf{\Theta}(t)\} \tag{21}$$

Eq. (21) is the expected change in the Lyapunov function over one time slot, given that the current state in time slot t is $\mathbf{\Theta}(t)$. Following the Lyapunov optimization approach (Neely, 2010), we incorporate the expected energy cost over one time slot, to both sides of Eq. (21), which leads to *drift-plus-penalty* term: $\Delta(\mathbf{\Theta}(t)) + V \cdot E\{C(t) \mid \mathbf{\Theta}(t)\}$, where control parameter $V > 0$ that represents an important weight on how much the IDC operator emphasizes energy cost minimization. Such a control decision can be motivated as follows: we want to make $\Delta(\mathbf{\Theta}(t))$ small to push queue backlog towards a lower congestion state, but we also want to make $E\{C(t) \mid \mathbf{\Theta}(t)\}$ small so that we do not incur large energy cost expenditure. We thus decide according to the above weighted sum.

Then, a key derivation step is to obtain an upper bound on this term. The following lemma defines such an upper bound for our case.

Lemma 1. For any possible action under constraints (15b) - (15f) that can be implemented at slot t, we have

$$\begin{aligned} &\Delta(\mathbf{\Theta}(t)) + V \cdot E\{C(t) \mid \mathbf{\Theta}(t)\} \\ &\quad \leq D + V \cdot E\{C(t) \mid \mathbf{\Theta}(t)\} \\ &\quad + Q(t) \cdot E\{a(t) - b(t) \mid \mathbf{\Theta}(t)\} \\ &\quad + Z(t) \cdot E\{u(t) - u^{av} \mid \mathbf{\Theta}(t)\} \end{aligned} \tag{22}$$

where

$$D = \frac{1}{2} \cdot (A_{max}^2 + B_{max}^2) + \frac{1}{2} \cdot max[(1-u^{av})^2, (u^{av})^2 \tag{23}$$

Proof. According to Eq. (20), we have

$$\begin{aligned} L(\mathbf{\Theta}(t+1)) - L(\mathbf{\Theta}(t)) &= \frac{1}{2}[Q(t+1)^2 - Q(t)^2] \\ &+ \frac{1}{2}[Z(t+1)^2 - Z(t)^2] \end{aligned} \tag{24}$$

Then, using the fact that for any real number x, $(max[x,0])^2 \leq x^2$, we have

$$\begin{aligned} Q(t+1)^2 - Q(t)^2 &\leq a(t)^2 + b(t)^2 \\ &+ 2Q(t) \cdot [a(t) - b(t)] \end{aligned} \tag{25}$$

In the same way, we get:

$$Z(t+1)^2 - Z(t)^2 \le (u(t)-u^{av})^2 + 2Z(t)\cdot[u(t)-u^{av}] \tag{26}$$

Then,

$$\begin{aligned}\Delta(\boldsymbol{\Theta}(t)) &= E\{L(\boldsymbol{\Theta}(t+1)) - L(\boldsymbol{\Theta}(t)) \mid \boldsymbol{\Theta}(t)\} \\ &\le \frac{1}{2}E\{[a(t)^2 + b(t)^2] \mid \boldsymbol{\Theta}(t)\} \\ &+ Q(t)\cdot E\{[a(t)-b(t)] \mid \boldsymbol{\Theta}(t)\} \\ &+ \frac{1}{2}E\{(u(t)-u^{av})^2 \mid \boldsymbol{\Theta}(t)\} \\ &+ Z(t)\cdot E\{[u(t)-u^{av}] \mid \boldsymbol{\Theta}(t)\}\end{aligned} \tag{27}$$

As $a(t) \le A_{max}$, $b(t) \le B_{max}$, and $0 \le u(t) \le 1$, we have

$$\begin{aligned}&\frac{1}{2}E\{[a(t)^2 + b(t)^2] \mid \boldsymbol{\Theta}(t)\} + \frac{1}{2}E\{(u(t)-u^{av})^2 \mid \boldsymbol{\Theta}(t)\} \\ &\le \frac{1}{2}(A_{max}^2 + B_{max}^2) + \frac{1}{2}max[(1-u^{av})^2, (u^{av})^2]\end{aligned} \tag{28}$$

Then, we get

$$\begin{aligned}\Delta(\boldsymbol{\Theta}(t)) \le D + Q(t)\cdot E\{a(t)-b(t) \mid \boldsymbol{\Theta}(t)\} \\ + Z(t)\cdot E\{u(t)-u^{av} \mid \boldsymbol{\Theta}(t)\}\end{aligned} \tag{29}$$

Now adding $V\cdot E\{C(t) \mid \boldsymbol{\Theta}(t)\}$ to both sides prove the lemma 1.

Following the design principle of Lyapunov framework, the underlying objective is to minimize the upper bound of the *drift-plus-penalty* term. Rather than directly minimize *drift-plus-penalty* term every slot t, our strategy actually seeks to minimize the bound given in the right-hand-side of (22). This is done via the framework of opportunistically minimizing a conditional expectation. Then, our algorithm finally minimizes the R.H.S of Eq. (22) by minimizing the following simplified term:

$$\begin{aligned}&\text{Minimize} \\ &V\cdot C(t) - Q(t)\cdot b(t) + Z(t)\cdot u(t) \\ &= V\cdot P(R(t))\cdot p(t) - Q(t)\cdot b(t) \\ &+ Z(t)\cdot\frac{1}{\lambda}b(t)\cdot r(t)\end{aligned} \tag{30a}$$

Subject to (15d), (15e) and (15f) (30b)

As $Q(t)$, $Z(t)$ and $p(t)$ can be observed at the beginning of every time slot t, there are only three variables in Eq. (30a), namely $b(t)$, $r(t)$ and $R(t)$, respectively. Nevertheless, if we determine how many tasks to be processed and which security levels to be selected for these tasks in time slot t, that is if we determine the parameters $b(t)$ and $r(t)$, the total workload of these tasks can be computed by Eq. (4). Then, we can calculate how many resources $R(t)$ should be provided by IDC. Finally, the value of Eq. (30a) can be got.

Note that variable $b(t)$ and $r(t)$ are discrete and there are three authentication services, seven integrity services and eight confidentiality services in the real-world applications (Xie and Qin, 2006). So, there are k possibilities for risk rate $r(t)$ in every time slot t, i.e. $k = 4\times 8\times 9$. Furthermore, variable $b(t)$ only has $(n(t)+1)$ choices for the FIFO queue system in time slot t. Hence, we can use the enumeration method to minimize Eq. (30a) subjects to constraint (30b).

The pseudo code of ECM algorithm is outlined in Figure 2. Note that all tasks have the same security services in time slot t. Therefore, for a fixed value $b(t) \in \{0,1,2,...,n(t)\}$ in time slot t, we calculate all the security levels profile and then select the local optimal profile which can minimize the value of Eq. (30a) (lines 5-13). Then, we enumerate $(n(t)+1)$ possibilities for all the tasks in the queue system to get access to the global minimization energy cost (lines 3-18). Finally, the IDC operator processes tasks according to optimal number of tasks, security levels profile and required resource and updates the actual queue $Q(t+1)$ and virtual queue $Z(t+1)$ at the end of time slot t (lines 19-20). We can conclude that the time complexity of ECM algorithm by enumeration method is $O(kn)$ in time slot t, where $n = n(t)$, which is polynomial associated with $n(t)$ in current queue $Q(t)$.

Considering a fixed V, if we do not want to process any task in time slot t, that is $b(t) = 0$, we have $R(t) = 0$, and then the expression of Eq. (30a) is zero. As we only minimize the Eq. (30a), the IDC operator executes the tasks when the value of Eq. (30a) is negative. It happens when either the electricity price $p(t)$ is low, or the queue $Q(t)$ is already congested in time slot t. Therefore, our ECM algorithm will process tasks in the following conditions: 1) when the electricity price $p(t)$ is low enough, the IDC operator will catch the chance to execute more tasks with low risk rate; 2) when the queue $Q(t)$ is congested, tasks must be finished to guarantee the queue stability.

4.2 Performance Analysis

The performance bounds of ECM algorithm are stated in the following theorem.

Theorem 1. Assume that the task arrival rate λ is strictly within the network capacity region $\boldsymbol{\Lambda}$, and the

ECM algorithm is applied at each time slot t. For any control parameter $V > 0$, it generates the time-average energy cost $\overline{C}$ and queue backlog $\overline{Q}$ satisfying that:

$$\overline{C} = \limsup_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} E\{C(\tau)\} \le C^* + \frac{D}{V} \tag{31}$$

$$\overline{Q} = \limsup_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} E\{Q(\tau)\} \le \frac{D + VC^*}{\varepsilon} \tag{32}$$

where D and ε are positive constants, and C^* is the theoretical optimal time-average energy cost.

Proof. Since the arrival process is strictly within the network capacity region, there exists one stationary randomized scheduling policy that can stabilize the queue (Neely, 2010), which satisfies the following properties:

$$E\{C(\tau)\} = C^* \tag{33}$$

$$E\{u(\tau) - u^{av}\} \le 0 \tag{34}$$

$$E\{a(\tau) - b(\tau)\} \le -\varepsilon \tag{35}$$

For any slot τ, by applying Eqs. (33), (34) and (35) to Eq. (22), we have:

$$\begin{aligned} &\Delta(\mathbf{\Theta}(\tau)) + V \cdot E\{C(\tau) \mid \mathbf{\Theta}(\tau)\} \\ &\quad \le D - \varepsilon \cdot Q(\tau) + V \cdot C^* \end{aligned} \tag{36}$$

Taking the expectation of Eq. (36) with respect to the distribution of $Q(\tau)$ and applying the iterative expectation law, we get

$$\begin{aligned} &E\{L(\mathbf{\Theta}(\tau+1)) - L(\mathbf{\Theta}(\tau))\} + V \cdot E\{C(\tau)\} \\ &\quad \le D - \varepsilon \cdot E\{Q(\tau)\} + V \cdot C^* \end{aligned} \tag{37}$$

Summing the series over all time slots $\tau \in \{0, 1, ..., t-1\}$ and using the law of telescoping sums yields:

$$\begin{aligned} &E\{L(\mathbf{\Theta}(t))\} - E\{L(\mathbf{\Theta}(0))\} + V \cdot \sum_{\tau=0}^{t-1} E\{C(\tau)\} \\ &\quad \le (D + V \cdot C^*) \cdot t - \varepsilon \cdot \sum_{\tau=0}^{t-1} E\{Q(\tau)\} \end{aligned} \tag{38}$$

Rearranging terms and neglecting non-negative terms when appropriate, it is easy to show that the above inequality directly implies the following two inequalities for all $t > 0$:

$$\frac{1}{t} \sum_{\tau=0}^{t-1} E\{C(\tau)\} \le C^* + \frac{D}{V} + \frac{E\{L(\mathbf{\Theta}(0))\}}{Vt} \tag{39}$$

$$\frac{1}{t} \sum_{\tau=0}^{t-1} E\{Q(\tau)\} \le \frac{D + VC^*}{\varepsilon} + \frac{E\{L(\mathbf{\Theta}(0))\}}{\varepsilon t} \tag{40}$$

where Eq. (39) follows by dividing Eq. (38) by Vt, and Eq. (40) follows by dividing Eq. (38) by εt.

Algorithm 1: ECM algorithm.

BEGIN
01. Set $minC = \infty$ to record the minimum energy cost;
02. Use $b^*(t)$, $(sl^{a^*}, sl^{g^*}, sl^{c^*})$ and $R^*(t)$ to record the optimal number of tasks, security levels profile and required resource under minimum energy cost;
03. **for** $b(t) = 0$ to $n(t)$ in time slot t
04. Set $Cost(b(t)) = \infty$ to record the local minimum energy cost;
05. **for** any security levels profile (sl^a, sl^g, sl^c)
06. Calculate the total workload $\sum_{i=1}^{b(t)} W_i$ of $b(t)$ tasks according to Eq. (4);
07. Get $R(t)$ based on condition constraint (15d);
08. Compute the value *value* of Eq. (30a);
09. **if** $value < Cost(b(t))$
10. Set $Cost(b(t)) = value$;
11. Record (sl^a, sl^g, sl^c) and $R(t)$;
12. **end if**
13. **end for**
14. **if** $Cost(b(t)) < minC$
15. Set $minC = Cost(b(t))$;
16. Update the $b^*(t)$, $(sl^{a^*}, sl^{g^*}, sl^{c^*})$ and $R^*(t)$;
17. **end if**
18. **end for**
19. IDC operator conduct processing actions according to $b^*(t)$, $(sl^{a^*}, sl^{g^*}, sl^{c^*})$ and $R^*(t)$;
20. Update actual queue $Q(t+1)$ and virtual queue $Z(t+1)$ when the current time slot t ends according to the Eq. (14) and Eq. (16) respectively.
END

Figure 2: The pseudo code of ECM algorithm.

Taking limits of the above as $t \to \infty$ proves Eqs. (31) and (32).

Theorem 1 can be understood as follows: If for any parameter $V > 0$, we can use the ECM algorithm to ensure the drift condition (36) is satisfied on every time slot, then the time average expected penalty satisfied Eq. (31) and hence is either less than the target value C^*, or differs from C^* by no more than the value D/V, which can be made arbitrarily small as V is increased. However, the time average queue backlog bound increases linearly in the V parameter, as shown by Eq. (32). This presents a cost-backlog tradeoff of $[O(1/V), O(V)]$. Such a cost-delay tradeoff allows ECM algorithm to make flexible design choices according to different application types and user contexts.

5 PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed algorithm based on real-world electricity prices.

5.1 Experimental Setup

System parameters Suppose that an IDC has $N = 10000$ servers, and power function $P(R(t))$ is we modelled as follows:

$$P(R(t)) = N \cdot (\alpha \cdot f^3(t) + P_{idle}) \tag{41}$$

In Eq. (41), α and P_{idle} are constants determined by IDC. Specifically, P_{idle} is the average idle power consumption of a server, and $\alpha \cdot f^3(t) + P_{idle}$ gives the power consumption of a server running at computing frequency $f(t)$. Then, the resource capacity of the IDC is $R(t) = N \cdot f(t)$ (in *basic resource unit*), where the computing frequency is in the range [1.2, 3.2] (Cao and Zhu, 2013). In our experiments, we choose $\alpha = 6.1$ and $P_{idle} = 100\text{W}$ such that the peak power consumed by a server is 250W. The model (41) is based on the measurements reported in (Gandhi et al., 2009; Yao et al., 2014).

Task workload Suppose that the number of tasks arrive in each slot $a(t)$ follows a Poisson distribution with parameter 5 and the execution workload follows a uniform distribution in the range [1000, 4000] (in *basic resource unit*). In order to meet the security requirement of each task, the IDC should process the security workload. The risk coefficients of three attacks are set $\lambda^a = 3.0$, $\lambda^g = 2.5$ and $\lambda^c = 1.8$, respectively. For the integrity service and confidentiality service, the workload function (in *basic resource unit*) is devised as follows.

$$F^k(sl^k, d^k) = \beta^k \cdot sl^k \cdot d^k, \quad k \in \{g, c\} \tag{42}$$

We can see that Eq. (42) satisfies the property 1. As to authentication service, the workload function is represented by Eq. (43).

$$F^k(sl^k) = \beta^k \cdot sl^k, \quad k \in \{a\} \tag{43}$$

For each arrived task, the protected data d^k is in the range [0.1, 1] GB, and $\beta^a = 1600$, $\beta^g = 2400$ and $\beta^c = 800$. These parameters are derived and deduced from (Xie and Qin, 2006).

Electricity Price We downloaded the hourly electricity prices of Palo Alto in real-time electricity market (Nyiso, 2015), and the time horizon we consider in this paper is from June 1 to June 30, 2015. To fully exploit the cost savings due to temporal power price variations, we would have preferred to have prices at a time granularity that exhibits high variability, for example, the length of a time slot is set to 5 minutes (Qureshi et al., 2009). However, since we had access to only the hourly prices, we use interpolation to generate prices at 5-minute intervals (Yao et al., 2014). Thus, the time horizon in the evaluations is 8640 slots.

Algorithms in Comparison The following four algorithms are compared in terms of energy cost and queue delay in the experiments:

***Algo*-1:** The Lyapunov optimization technique is not utilized in this algorithm. Thus, arriving tasks are not queued. It starts to execute tasks when they are received. Moreover, these tasks are executed without security services.

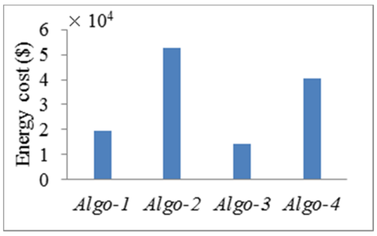
***Algo-2*:** This algorithm starts to execute all arriving tasks when they are received. However, each task requires security services to ensure its security execution. Furthermore, all the levels of service are set to 1.

***Algo-3*:** It uses our proposed ECM algorithm but with no risk rate constraint, i.e., $u^{av} = 1$. Different from *Algo-1* and *Algo-2*, the arrived tasks are queued in the IDC, which will be processed when the electricity price is low or the queue is congested.

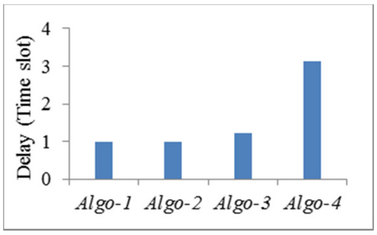
***Algo-4*:** This is our ECM algorithm, the purpose of which is to minimize the total energy cost with risk rate constraint for IDC.

5.2 Performance Comparison of Four Algorithms

We fix the parameter $V = 10$ and $u^{av} = 0$ for *Algo-4* and conduct the four algorithms in TEC and average delay. As shown in Figure 3 (a), we can make the following observations about TEC: 1) Compared with *Algo-1* and *Algo-2* respectively, *Algo-3* and *Algo-4* have the Lower TEC. This is because *Algo-3* and *Algo-4* uses the Lyapunov optimization technique to minimize the energy cost. The arrived tasks are queued in the IDC, which can be processed when the electricity price is low, i.e., the IDC operator can fully exploit the temporal diversities of electricity price; 2) *Algo-2* exhibits more energy cost than *Algo-1*. This is reflected by the fact that each task in *Algo-2* requires security services to ensure its security execution, which will incur a great amount of security workload and power demand for IDC (see Section 3.3). There is the same relationship between *Algo-3* and *Algo-4*.

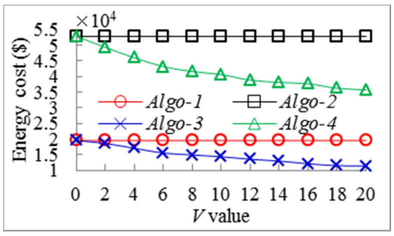


(a) Energy cost

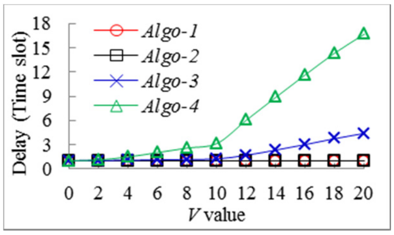


(b) Delay

Figure 3: Energy cost and delay of four algorithms.



(a) Energy cost



(b) Delay

Figure 4: Energy cost and delay under different V.

As for average delay shown in Figure 3 (b), *Algo-1* and *Algo-2* have the same and lowest delay, which results from the fact that arrived tasks are not queued, and IDC operator executes these tasks in the same slot when they are received. The *Algo-4* tends to have the longer average delay due to two reasons that: 1) arrived tasks in the queue are waiting for low electricity price; 2) security services result in more workload while IDC only processes fewer tasks in one time slot, which increases the length of task queue. The *Algo-3* has no security services but with task queue, the delay of which is medium.

5.3 Performance Vary under Different Parameters

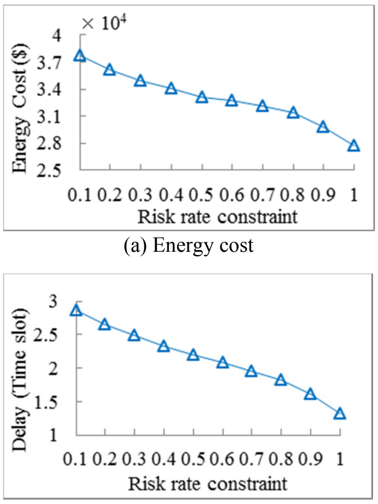
Figure 4 illustrates the performance of four algorithms under varying control parameter V. As *Aglo-1* and *Aglo-2* are independent of parameter V, we plot them as baselines in contrast with *Algo-3* and *Algo-4*. The parameter V controls the energy-delay tradeoff of *Algo-3* and *Algo-4*. As shown in Figure 4, given $u^{av}=0$, the TEC drops and the time-average delay grows as V goes from 0 to 20. The TEC of *Algo-1* and *Algo-2* are always larger than *Algo-3* and *Algo-4*, respectively, while they are equal when $V=0$. This is because security services incur lots of energy cost, and we only care about the queue delay when parameter V is set to 0. Note that energy cost falls quickly at the beginning and then tends to descend slowly while the time-averaged queue backlog grows linearly with V. This finding confirms the $[O(1/V),O(V)]$ energy-delay tradeoff as captured in Eqs. (31) and (32). Particularly, there exists a spot of V (e.g., $V=10$), beyond which increasing V leads to marginal energy conservation yet consistently growing delays.

5.4 Impact of Risk Rate Constraint

For purpose of revealing the impact of risk rate constraint of our ECM algorithm, we fix $V=10$ and vary u^{av} from 0.1 to 1. The performance effects of varying risk rate constraint are reported in Figure 5. It can be seen that the TEC and delay become lower as risk rate u^{av} increases. This phenomenon can be explained as follows: given a large risk rate constraint, the workload of security service is small according to Eqs. (1) and (2). Then, we need less electricity energy to execute the arrived tasks. What is more, The IDC operator can process more tasks in one time slot under the same computing resource that leads to lower average delay. Overall, though larger risk rate constraint will reduce the TEC and delay, the tasks may experience more threats and attacks when being executed in IDC.

5.5 Impact of Three Risk Coefficients

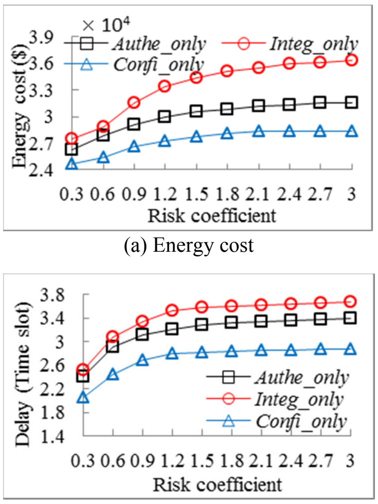
As mentioned in Section 3.4, the risk rate is highly correlated with the risk coefficient. This section is focused on the performance impact of the three risk coefficients on our ECM algorithm. We fix V to be 10 and use shortening *Authe_only*, *Integ_only* and *Confi_only* to represent authentication service only,



(a) Energy cost

(b) Delay

Figure 5: Energy cost and delay under different risk rate constraints.



(a) Energy cost

(b) Delay

Figure 6: Impact of three risk coefficients.

integrity service only and confidentiality service only, respectively. *Authe_only* means that there is only authentication service for tasks, and this is the same interpretation with other two shortenings.

The simulation results are given in Figure 6 for three risk coefficients. Overall, the *Confi_only* achieves the lowest TEC and delay, *Authe_only* has the medium performances and *Integ_only* performs the worst. This can be explained by the fact that we set $\beta^c < \beta^a < \beta^g$, and a larger parameter β will lead to more security workload. We can also see from Figure 6 that the three curves are higher slope when parameter $\lambda^k \le 1.5, k \in \{a,g,c\}$, beyond which curves become flat. The explanation is that the risk rate changes dramatically when the risk coefficient varies in a small range in terms of Eq. (5), then the TEC and delay change with the same pace. In a word, different risk coefficients make different impacts on our energy cost minimization framework.

6 CONCLUSION AND FUTURE WORK

In this paper, we propose a long-term energy cost minimization (ECM) algorithm for an internet data center in deregulated electricity markets. We formulate the stochastic optimization problem taking the temporal diversity of electricity price and risk rate constraint into account. Then, an operation algorithm is designed to solve the problem by Lyapunov optimization framework, which offers provable energy cost and delay guarantees.

As a future work, we are going to consider some new aspects in better usage of power in IDC, such as renewable energy, energy storage, battery and so on. We also plan to exploit spatial variations in the workload arrival process and the power prices to reduce energy cost for IDC.

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