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Optimization Of Operational Costs In Data Centers

Shaoming Chen
Louisiana State University and Agricultural and Mechanical College, schen26@lsu.edu

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ABSTRACT

The electricity cost of cloud computing data centers dominated by server power and cooling power is growing rapidly. To tackle this problem, inlet air with moderate temperature and server consolidation are widely adopted. However, the benefit of these two methods is limited due to conventional air cooling systems ineffectiveness caused by re-circulation and low heat capacity. To address this problem, hybrid air and liquid cooling, as a practical and inexpensive approach, has been introduced. In this work, we quantitatively analyze the impact of server consolidation and temperature of cooling water on the total electricity and server maintenance costs in hybrid cooling data centers. To minimize the total costs, we proposed to maintain sweet temperature and ASTT (available sleeping time threshold) by which a joint cost optimization can be satisfied. By using real world traces, the potential savings of sweet temperature and ASTT are estimated to be average 18% of the total cost while 99% requests are satisfied compared to a strategy which only reduces electricity cost. The co-optimization is extended to increase the benefit of the renewable energy and its profit grows as the more wind power is supplied.

CHAPTER 1. INTRODUCTION

The total cost of ownership (TCO) in cloud computing data centers consists of onetime capital costs incurring only at the beginning or upgrade stage of data centers and monthly recurring operational costs including electricity cost, maintenance cost and salaries [3]. According to a recent report [2], the TCO is dominated by the operational costs, among which salaries are largely not a technical but an economic factor. Therefore, we focus on optimization of electricity and maintenance costs in this work.

The growth of the cost of electricity consisting of server power and cooling power outpaces expectations. In 2011, U.S. data centers spent about $7.4 billion in electric power among which server power and cooling power contribute significantly to the total [32]. Several studies try to throttle this increase, though few of them consider the cost of server maintenance.

Prior works employ two methods to reduce energy cost: increasing server consolidation and increasing inlet air temperature. Server consolidation has been widely adopted to gain high energy efficiency of server, keeping active servers in high utilization by turning off overprovisioned servers [34]. Dynamic Voltage and Frequency Scaling (DVFS) is also used to save server power [14]. However, the benefits of DVFS are shrinking because the leakage power is increasing and the voltage of processors is getting very close to its limit [26]. In addition, DVFS only reduces CPU power which merely amounts to 30% of server power [32]. Server consolidation remains as an effective and practical method to save server power.

Increasing inlet air temperature is a common method to reduce cooling power. Increasing inlet air temperature by just one degree can reduce cooling energy consumption by 2 to 5 percent [7]. However, the room of inlet air temperature can be raised is very limited due to the constraint of server temperature below the critical temperature. To keep the constraint with a low cost, there are several prior works advocating thermal-aware workloads placement which distributes workloads according to the thermal map of data centers [28]. Unfortunately, these methods hardly maintain energy efficiency of traditional air cooling when data centers are in high utilization [34]. Therefore, a novel cooling system is demanded.

The hybrid cooling system is proposed as a practical and inexpensive solution of liquid cooling [18]. It combines air and liquid cooling has been proposed and deployed in data centers such as Aquasar, the first hot water cooled supercomputer prototype [44]. The hybrid cooling system uses water to cool down high power density components such as processors and memory devices which dominate total heat dissipated in servers, while it uses air to cool down other auxiliary components which show low power density. In this way, the hybrid cooling system can remove a mass of heat from data center with less power than conventional air cooling.

In addition to the energy cost, the hardware maintenance cost is also considerable. According to a typical new multi-megawatt data center in the United States, the cost of server repair and maintenance is approximately 50% of the costs of server power and cooling power [3]. Disks are the most frequently replaced components based on the empirical data of a HPC data center. The cost of disk maintenance can be increased by server consolidation due to the limited start-stop cycles of disks [10], since server consolidation frequently turns off servers or switch servers between the active state and the sleeping state. Additionally, higher inlet water temperature increases the cost of CPU and memory maintenance, since every 10°C increase over 21°C decreases the lifetime reliability of electronics by 50% [31]. Therefore, we can balance the saving of the electricity costs and the increase of the costs of hardware maintenance by manipulating inlet water temperature and server consolidation.

On the other hand, the sustainability of data centers is becoming one of top concerns of their owners, as three years electricity bills of modern data centers grow over the server equipment cost [6]. The power sources are shifted toward renewable energies such as wind, solar, and tidal power, driven by soaring conventional energy price and the global warming. Wind power or tide power is integrated into our proposed optimization of electricity and server maintenance costs since wind energy is cheaper and widely used to power large-scale facilities [30].

The discussion of electricity and hardware maintenance costs drives us to propose our comprehensive framework covering these two costs. Integrating the models of electricity costs and hardware maintenance costs are non-trivial due to being studied separately by using different metrics. For example, the works focusing on electricity costs are likely to report their benefit in terms of power, while the works on hardware maintenance focus on expected lifetimes of hardware components. Although the two kinds of work are also studied in different scenarios, they interact with each other via inlet water temperature and server consolidation. Thus how to fuse the models reasonably in a framework is our most challenging task This framework distinguishes our work by optimizing these two costs together while other prior works[35][39]exclusively focus on electricity or hardware maintenance costs for data centers. Focusing on these two costs rather than one of them avoids categorizing our optimization as a sub-optimal solution for the total cost.

The contributions of our work are shown in the following.

• We set up analytical models for server power, cooling power and hardware maintenance in a hybrid cooling data center for quantitative evaluation. We build a comprehensive framework which covers evaluations of these costs. To our knowledge, none of the existing methods have addressed this issue. This framework provides foundations to optimize the total cost in hybrid cooling data centers.

• We propose a tradeoff between electricity and maintenance costs. In this work, we show that the typical optimizations (high inlet water temperature and aggressive server consolidation) reduce the electricity costs but increase the maintenance costs.

• To minimize the costs, we develop a joint optimization scheme based on server consolidation and dynamic optimal inlet water temperature. Our simulation results show that the method can gain considerable cost benefits.

• We extend our cost optimization to exploit the benefits of two kinds of renewable energies: wind power and tide power. Based on our experiments, it increases the cost saving of the renewable energies and this benefit grows as the more renewable energies are supplied.

The rest of our work is organized as follows: we propose the optimization of operational costs in data centers with hybrid cooling in chapter 2. In chapter 3, we extend the optimization in data centers with renewable energies. Finally, we conclude the work in chapter 4.

CHAPTER 2. OPTIMIZATION OF OPERATIONAL COSTS WITH HYBRID COOLING

2.1 Hybrid Cooling

Figure 2.1 shows the structure of hybrid cooling in modern data centers. The closed liquid loop between the chiller and the racks is designed to remove heat dissipation from the racks. The cool water in the loop absorbs heat dissipation from the racks, and returns back to the chiller with heat. In the closed liquid loop of a rack, the water is pumped into servers and cooled in the intermediate Heat Exchanger (HTX). The coolant water in a server flows through a liquid cooled plate and takes away power dissipated by processors and memory devices. Other auxiliary components such as disks, power supply, and chipsets on motherboard are still cooled by the air condition as traditional data centers since these components dissipate less power and, more importantly, exhibit lower power density compared to processors and DRAMs.

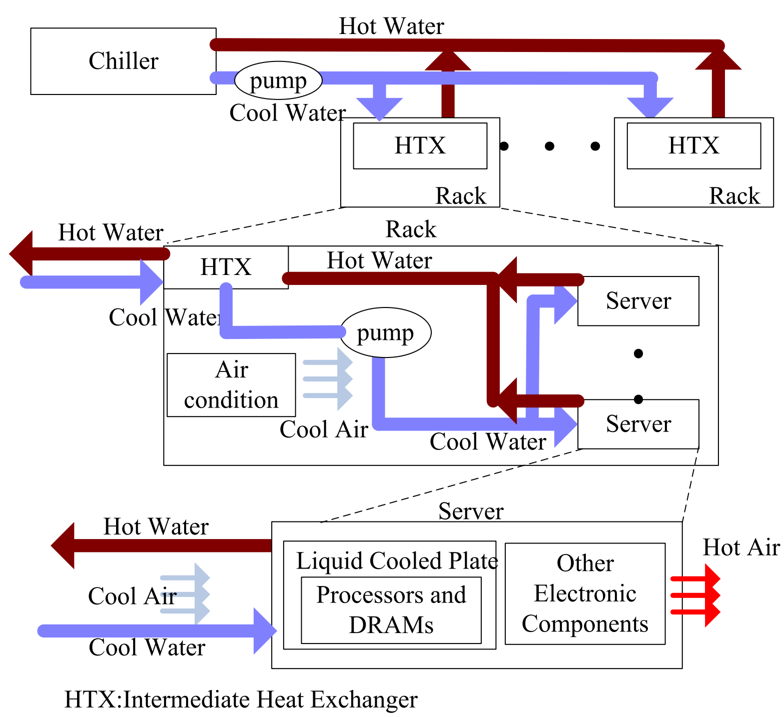

Figure 2-1. The structure of hybrid cooling

2.2 Cost Models

To optimize the electricity costs and the hardware maintenance costs, we setup the cost models which quantitatively estimate the impact of server consolidation and inlet water temperature on the costs when hybrid cooling is used.

2.2.1 Electricity Costs

The power of a typical data center includes server power, cooling power and power distribution loss. Power distribution loss is denoted by P_{PDL} which equals to 10% of load power in our experiment [41]. In the following context, we address the models related to the server power and cooling power.

Server Power Model: $P_{servers}$ consists of the aggregate power of active servers and the aggregate power of sleeping servers. The total power for servers is written as:

$$P_{servers} = \sum_{i=1}^{NAS} P_{Server}(i) + \sum_{j=1}^{NIS} P_{sleep}(j) \tag{1}$$

Here, NAS and NIS denotes the number of active servers and sleeping servers which are in the deep sleep state and consume 6 Watts power per server [2]. For an active server, the total power consists of the power of processors, the power of memory and the power of other components. The equation is listed as follows:

$$P_{Server} = \sum_{i=1}^{NS} P_{Processor}(i) + \sum_{j=1}^{NM} P_{Memory}(j) + P_{Other} \tag{2}$$

where NS and NM are denoted as the number of sockets and the number of DIMMs in a server. To simplify the equation, we assume that all servers in data centers have the same number of sockets and the number of DIMMs.

For the power model of components in a server ($P_{Processor}$, P_{Memory} and P_{Other}), we adopt the linear power model shown as follows:

$$P = (P_{TDP} - P_{idle}) * U + P_{idle} \tag{3}$$

where P_{TDP} and P_{idle} indicate the maximum power and idle power of components while U denotes server utilization.

The configuration of power model in a server is shown in Table 2-1. For processors, its idle power amounts to 10% of the TDP [11], while 4 HDD hard disks are assumed to be installed in the server to fit memory intensive applications. The specification is derived from a typical server [11].

Table 2-1. Configurations of simulated server

Server Configurations			
Part	#	TDP(w)	Idle power(w)
Processor	2	150W	15W
Memory	8	10W	5W
Others	-	124W	73.6W
Hybrid Cooling Configurations			
Parameter		Value	
T_{inlet_water} (°C)		25	
T_{inlet_air} (°C)		25	
V_w (GPM)		1	
η_{pump}		70%	
ΔP_w(psi)		4.2	
Thermal Reliability Configurations			
θ_{CP} (ºC/W)		0.3	
θ_{MP} (ºC/W)		4.75	
θ_p (ºC/W)		0.03	

(Table 2.1 continued)

Maintenance Cost Configurations	
Start-stop cycles for disks	40000
CPU maintenance price ($)	300
Disk maintenance price ($)	200
Memory maintenance price ($)	150

Cooling Power Model: According to the structure of the hybrid cooling, the cooling power can be divided into two parts: the liquid power and air cooling power:

$$P_{cooling} = P_{liquid\_cooling} + P_{air\_cooling} \tag{4}$$

To estimate cooling power, $E = \frac{Q}{COP}$ is employed where E denotes the energy to remove the heat dissipation Q from data centers and COP (Coefficient of Performance) which is defined as a metric to evaluate the efficiency of cooling system [28]. According to prior studies [2], COP_{air} (coefficient of performance) can be derived in the following equation: $COP_{air} = (0.0068 \times T\text{^}2 + 0.0008 \times T + 0.458)$ where T is the inlet air temperature.

The power of liquid cooling consists of the chiller power and the pump power [19]. The chiller efficiency for a typical chilled water system is written as: $COP_{liquid} = E/Q$ [4]. COP_{cooled} is written in terms of inlet water temperature: $COP_{liquid} = T * 0.18 - 0.4836$ based on the specification of water-cooled screw compressor chiller [8]. The water pump power is calculated by this equation [19]:

$$P_{pump} = N \times \frac{V_w \times \Delta P_w}{\eta_{pump}} \tag{5}$$

where N is the number of servers and V_w is the water volume flow rate. ΔP_w denotes the water side pressure drop based on the flow resistance. Finally, η_{pump} indicates the pump efficiency. Overall, the cooling power of the data center is calculated as follows:

$$P_{cooling} = \frac{Q_{liquid\ cooled}}{COP_{liquid}(T_{inlet\_water}) * t} + \frac{Q_{air\ cooled}}{COP_{air}(T_{inlet\_air}) * t} + P_{pump} \qquad (6)$$

where t is a time interval during which server components dissipate the heat $Q_{\text{liquid cooled}}$ and $Q_{\text{air cooled}}$. The heat $Q_{\text{liquid cooled}}$ is removed by the liquid cooling, while the heat $Q_{\text{air cooled}}$ is generated from other components in servers. Shown in the Table 2-1 is the configuration of hybrid cooling derived from [19]. The pump power of a server is 0.6 watt and is negligible compared to the chilling power.

Overall, the electricity cost of the data center is written as:

$$EC = K_{\$}\ (P_{servers} + P_{cooling} + P_{PDL}) \qquad (7)$$

Here, $K_{\$}$ respectively commercial KWH Billing Rate which comes to 9 cents/KWH as the default value.

2.2.2 The Costs of Hardware Maintenance

We focus on the maintenance costs of DRAM and CPU due to the high power density. In addition, we take the cost of disks maintenance into account, since their limited number of lifetime start-stop cycles is heavily impacted by frequent server consolidations, though hard disks have a low power density.

Thermal model**:** We have setup up thermal models to investigate the costs of processor and memory maintenance. The CPU temperature T_C is calculated as follows from [20]:

$$T_C = T_{inlet} + (\theta_{CP} + \theta_p) * Q_C \qquad (8)$$

Here, T_{inlet} is the inlet water temperature and Q_C is the power dissipated by the CPU. Thermal resistance of the processor package and TIM (Thermal Interface Material) layer is denoted by θ_{CP} with a value derived from [19]. The thermal resistance of cold plate which varies with water flow is denoted by θ_p, according to the specification of Lytron CP20 cold plates [19]. Regarding the reliability issue of CPU, there is a threshold temperature for processor chips as 90°C [19]. The temperature T_M for DRAM is given as follows:

$$T_M = T_{inlet} + (\theta_{MP} + \theta_P) * Q_{MP} \tag{9}$$

where Q_{MP} is the power dissipated by memory. The thermal resistance of the chip package of DRAM is denoted by θ_{MP} derived from [12]. There is a threshold temperature for DRAM as 85°C [23]. The characteristics of thermal package of DRAM, CPU and cold plates are listed in the Table 2-1.

Thermal reliability model of electronic devices**:** We can predict the lifetimes of electronic devices based on the thermal reliability models of electronic devices. Chip temperature and power are the main factors to determine the lifetimes of electronic de vices [15]. For memory, the lifetime prediction model is adopted [22]. MTTF (mean time to failure) is widely used to represents the predicted lifetime of electronic components for processors: $\mathrm{MTTF} = 1/\lambda$. For the prediction of the lifetime of processor and memory, λ is the number of failures per million hours, and calculated according to Military Handbook MIL-HDBK-217F [37].

$$\lambda = (C_1\pi_T + C_2\pi_E)\pi_Q\pi_L \tag{10}$$

$$\pi_T = 0.1\exp\left(\frac{-E_a}{8.617 \times 10^{-5}}\left(\frac{1}{T_p + 273} - \frac{1}{298}\right)\right) \tag{11}$$

Here, E_a is the effective activation energy (Ev) and T_P is the temperature of electronic devices. The parameters $(C_1, C_2, \pi_E, \pi_L, \pi_Q)$ are derived from [37]. We have scaled the lifetime of CPU and memory according to recent studies [22]. The lifetime of CPU is expected to be 7 years when chip temperature is 70 ºC [41], while the expected lifetime of 2GB DRAM is 5 years when its temperature is 65 ºC [22].

Maintenance Cost Models of Processor and DRAM**:** We evaluate the costs of processors and DRAM maintenance based on their thermal reliability is given as lows:$\mathrm{RC} = \textit{the cost of hardware maintenances} / \mathrm{MTTF}$.

For a time interval, MTTF is calculated based on their thermal reliability model with current chip temperature. The cost of a CPU, a disk and a memory maintenance are \$300, \$200 and \$150 respectively as shown in Table 2-1, according to the maintenance ranging from \$300 to \$150 [3]. Based on the thermal reliability model, the cost of CPU and memory maintenance in an active server is specified as follows:

$$RC_{Server} = \sum_{i=1}^{NS} RC_{Processor}(i) + \sum_{j=1}^{DM} RC_{Memory}(j) \tag{12}$$

Here, the costs of DRAM and CPU maintenance are increased by higher inlet water temperature. The auxiliary components are excluded from this model since they are still cooled down by air cooling. Their little heat dissipation, much lower power density and fixed inlet air temperature result in their little cooling power and their stable maintenance cost.

Maintenance Cost Model of Hard Disk**:** The lifetime of hard disks is heavily impacted by server consolidations due to the limited number of lifetime start-stop cycles [13], while the impact of utilization and temperature is still unclear [33]. On the other hand, switching on/off servers incurs relatively little maintenance cost of other components such as processors and memory compared with that of hard disks. The cost of disk maintenance is computed by the following equation:

$$RC_{Disk} = \frac{Price}{start - stop\ cycles} \tag{13}$$

As we know, the number of lifetime start-stop cycles for hard disks is 40000 [10]. Overall, the cost of hardware maintenance of data center is listed as follows:

$$RC = \sum_{n=1}^{ND} RC_{Disk}\,[NAS(t-1) - NAS(t)]^{+} + \sum_{k=1}^{NAS} R_{Server}(k) \tag{14}$$

$$[A]^{+} = A\ if\ A > 0\ or\ [A]^{+} = 0\ if\ A \le 0$$

where ND and $\mathrm{NAS}(t)$ respectively denotes the number of disks in a server and the number of active servers in the data center at the time t. $[\mathrm{NAS}(t) - \mathrm{NAS}(t-1)]^+$ represents the number of servers which have been turned off.

Consequently, we have set up models for electricity cost and the cost of hardware maintenance to evaluate our approach which optimizes the total cost. The models have been validated with the costs of our campus data centers. We have listed all key notations for readers in Table 2-2.

Table 2-2. Key notation

Notation	Definition
$P_{servers}$	The power consumption of all servers
P_{PDL}	The power distribution loss
$P_{Server}(i)$	The power consumption of an active server at time i
$P_{sleep}(i)$	The power consumption of a sleeping server at time i
$P_{Processor}(i)$	The power consumption of a processor at time i
$P_{Memory}(i)$	The power consumption of a memory module at time i
P_{Other}	The power consumption of auxiliary components in a server memory module at time i
NAS	The number of active servers
NIS	The number of sleeping servers
NS	The number of sockets in a server
NM	The number of DIMMs in a server
MINS	The minimal demanded number of active servers
$K_{\$}$	Commercial KWH Billing Rate
TC	The total costs
P_{cooling}	The cooling power
$P_{\mathrm{liquid\_cooling}}$	The liquid cooling power
$P_{\mathrm{air\_cooling}}$	The air cooling power
RC_{Server}	The maintenance cost for a server related to processors and memory
$RC_{Processor}(i)$	The maintenance cost for a processor

(Table 2.2 continued)

Notation	Definition
$RC_{Memory}(i)$	The maintenance cost for a memory
RC_{Disk}	The maintenance cost for a disk
ND	The number of disks in a server
T_C	The working temperature of a processor
T_M	The working temperature of a memory
T_{inlet_water}	The temperature of inlet water to cool down processors and memory

2.3 Cost Optimization in Data Centers

We formulate the total cost in equation (15) based on the equations (7) (14) with the constraints. Focusing on the operational cost of data centers, we pick up a typical specification for our heuristic data center shown in Table 2-1.There are two important decision variables $T_{inlet_water}$and NAS, while other variables are determined by available servers, server performance and characteristics of traces, which are also treated as parameters. For example, NS denotes the total number of servers, while MINS denotes the minimal required number of active servers which is determined by traces. Our objective is to minimize the total cost with the constraints:

$$\min \{TC = \sum_{n=1}^{ND} RC_{Disk} * [\mathrm{NAS(t-1)} - \mathrm{NAS(t)}]^{+} + \sum_{i=1}^{NAS} \mathrm{RC_{Server}(i)} + EC\} \quad (15)$$

It is subjected to $T_C \leq 90$ °C and $T_M \leq 85$ °C $\mathrm{MINS} \leq \mathrm{NAS} \leq \mathrm{NS}$ .The space of feasible solutions of this discrete optimization is too large, resulting in that exhaustively searching the global optimal solution is impossible. To optimize the total cost of electricity and hardware maintenance, we proposed to trace local optimal solution by dynamically manipulating T_{inlet_water} and NAS corresponding to the fluctuation of workloads.

Our Cost Optimization dynamically tracks the optimal T_{inlet_water} and NAS indi vidually. The optimal T_{inlet_water} is tracked to minimize the sum of the cooling cost and the maintenance costs given the utilization of servers. On the other hand, NAS is determined based on the minimal number of servers bounded by QoS in up-coming intervals, which balances the cost of server power and the hardware maintenance cost. Without the maintenance cost of hard disks, the optimization would increase the utilization to the upper bound as the optimal utilization within the constraints, consolidating jobs into few servers to save the electricity cost which surpasses the maintenance costs for CPU and DRAM based on the default electricity price. Including the maintenance cost of hard disks, the optimization adjusts the number of servers to swing it between tracking the optimal utilization and becoming constant under the constraint of QoS. It reduces the sum of the electricity cost of server power and the maintenance cost of hard disks. The optimal utilization can declines if the electricity price falls, which may happen when the energy resource becomes cheaper.

2.3.1 The Overview of Cost Optimization System

For the manipulation of $T_{inlet}$and NAS, we proposed a structure shown in Figure 2-2. In this structure, there are four modules: Workload Prediction, Server Monitor, Server Manager and Temperature Manger, working together to reduce the total cost. The workload prediction collects request history and predicts future request trend, and the future minimal required number of active servers. The server monitor collects the temperature and utilization information of servers and estimates the cost of hardware maintenance. Acquiring the average server utilization from the server monitor, the temperature manager adjusts inlet water temperature. The Server manager dynamic allocates servers according to the predicted future minimal required number of active servers.

2.3.2 Optimal Inlet Water Temperature

To investigate the impact of the inlet water temperature on the total cost, we divide the total cost into two parts: the cost of cooling power and CPU and memory maintenance which are affected by the inlet water temperature, and the other costs which are unaffected denoted by C.

$$TC = K_{\$} * P_{cooling} + \sum_{i=1}^{NAS} RC_{Server}(i) + C \quad (16)$$

As the inlet water temperature increases, P_{cooling} decreases based on the function of COP, while RC_{Server} increases at the same time according to equations (8)-(12). There should be an optimal temperature to balance the cost of cooling power and the costs of CPU and memory maintenance given the utilization. The optimal temperature (or sweet temperature) is adjusted according to workloads since the two costs also vary with the change of workloads.

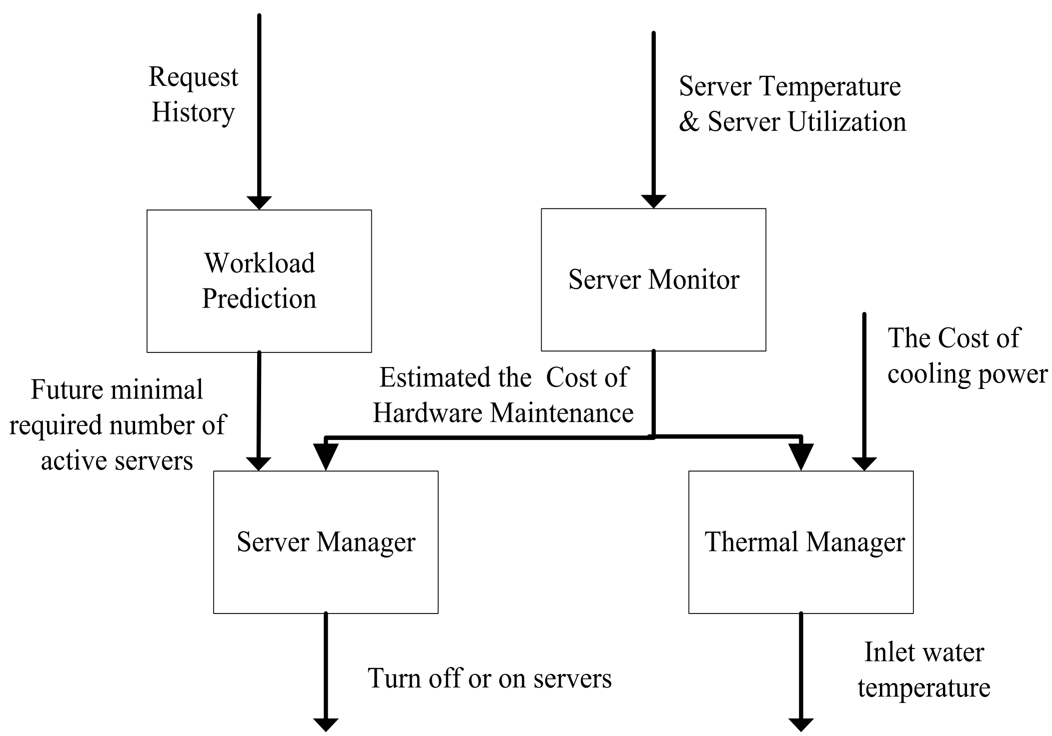

Figure 2-2. The overview of costs optimization system

2.3.3 The Impact of Server Consolidation

The other substantial variable NAS is facilitated by server consolidation which lively migrate jobs cross servers, with the upper bound of available servers and the low bound of service level agreement. Under these constraints, its cost and benefit are investigated in the following.

The cost of Server Consolidation**:** It is well known that server consolidation could save the electricity cost. Unfortunately, it increases the cost of disk maintenance, according to equation (14). Furthermore, servers waste energy during the transition between the active state and the sleeping state. We formulate the cost for server consolidation denoted by C_{cs}. The cost C_{cs} per a server is calculated as follows:

$$C_{cs} = \sum_{j=1}^{ND} RC_{Disk} + P_{max} * T_T * K_{\$} \tag{17}$$

where T_T is the time of the two transitions (switching from active to sleep and back) including two job migrations (20 seconds for one [10]) and two transitions between the active state and sleeping state (5 seconds for ACPI S3 state [25]). Therefore, T_T is estimated to be 50 seconds which is relatively small compared with the 5 minutes which it takes to change the state of a server in our experiment. P_{max} and $K_{\$}$ respectively represent the maximum power for a server and denotes commercial KWH Billing Rate. Note the server consolidation implicitly increases the maintenance costs of CPU and DRAM, by increasing the utilization and the temperature of active servers. They are excluded from C_{cs} since they are far less than the benefit of server consolidation.

The benefit of Server Consolidation**:** The reward of server consolidation depends on the length of server sleeping time for once turning off. In other word, the benefit is determined by the length of the period of turning off servers without violation of user level agreement. The length of this period is referred as available sleeping time (AST) which indicates the maximal server sleeping time. Thus, the benefit of turning off N servers is denoted by $B_{sleeping} \times AST \times N$. Here, $B_{sleeping}$ denotes the benefit of turning off a server for a minute.

To optimize server consolidation, we define available sleeping time threshold (ASTT) as follow:

$$ASTT = \frac{C_{cs}}{\mathrm{B}_{\mathrm{sleeping}}} \tag{18}$$

When the available sleep time of servers is longer than ASTT, the servers should be turned off. Otherwise, the server should keep running. We design an algorithm shown in Figure 2-3 based on the concept. Generally, the algorithm conservatively turns off servers to mitigate the cost of server consolidation.

In this algorithm, the decision of turning off servers requires the knowledge of Future Minimal Required Number of Active Servers (FMRNAS) which is bound by the constraint of service level agreement (SLA).The performance of this algorithm depends on how accurately FMRNAS is predicted. Therefore, we will introduce two different predictions combined with the algorithm in the following sections.

```
//NAS : the Current Number of Active Servers
if NAS < FMRNAS [T]
        NAS = FMRNAS [T]
Else
        // Turn off servers
        If  NAS > Max(FMRNAS [T,T+ ASTT])
        // Turn off(NAS - Max(FMRNAS [T,T+ ASTT])) servers
                NAS = Max(FMRNAS [T,T+ ASTT])
        Else
                pass
```

Figure 2-3. The algorithm based on ASTT

ASTT-P Available sleeping time threshold based on a perfect prediction**:** Firstly, we assume that we have a perfect predictor which indicates FMRNAS accurately. Given this knowledge, ASTT-P is designed to minimize the total cost by selecting an available sleeping threshold without the impact of inaccurate predictions. The exact value of optimal available sleeping threshold is impossibly obtained by solving equation (18) since $B_{sleeping}$ is slightly affected by other factors such as inlet water temperature.

ASTT-AR: Available Sleeping time threshold based on the autoregressive model (AR model)**.** The adopted prediction based on the autoregressive model [42] which is widely used for pattern prediction is listed in the following equation to estimate FMRNAS:

$$\dot{SN}(T) = (K + 1)(C + \sum_{i=1}^{a} A_i * SN(T - i)) \;\; i = 1 \cdots a \tag{19}$$

where $\dot{SN}(T)$ denotes predicted FMRNAS at time T while $SN(T - i)$ denotes PMRNAS at time $(T - i)$. C and A_i are tuned to reduce overprovision servers and guarantee the response time in offline. K is updated according to the percentage of requests whose response time is satisfied. When the percentage is below the requirement, K increases to reserve more servers to handle spike requests. Otherwise, K is decreased. The goal in this work is to satisfy more than 99% requests. In our work, we focus on the benefit of ASTT by utilizing the mature pattern prediction, though it might be replaced by advanced tools. We show the percentage of satisfied requests to prove this algorithm can guarantee the QoS, even if the performance of the prediction is poor. The algorithm can keep more servers online by increasing K when the prediction is inaccurate, but increases the costs slightly. It explains the performance lose between ASTT-P and ASTT-AR.

In the following section, the model of a data center is built up to quantitatively evaluate the benefit of sweet temperature and ASTT.

2.4 Experiment Setup

2.4.1 Data Center

Recalling the models related to the costs of electricity and hardware maintenance, we combined them with server performance model and real traces to simulate our prototype data center which consists of 1024 servers cooled by hybrid cooling.

Server performance model & response time analysis**:** We assume a server in our data center provides 2.6 Gbytes/sec service rate and the mean of response time should be bound by 6 ms for SLA [10]. To calculate the FMRNAS at a time interval, we use GI/G/m model [5] to determine how many servers can satisfy a demand based on the following equation:

$$\widetilde{W} = \frac{1}{\mu} + \frac{P_m}{\mu(1-\rho)} * \left(\frac{C_A^2 + C_B^2}{2m}\right) \tag{20}$$

$$P_m = \rho^{\frac{m+1}{2}} \text{ if } \rho \leq 0.7$$

$$P_m = \frac{\rho^m + \rho}{2} \text{ if } \rho > 0.7$$

where $\widetilde{W}$ is the mean response time. $1/\mu$ is the mean service time of a server. $\rho = \frac{\lambda\varphi}{mf}$ is the average utilization of servers. $\lambda, \varphi,$. $C_A$and C_B are derived from trace characteristics [2]. We use this performance server and response time model to acquire the minimal required number of active servers at every time slot. For a time interval, we choose 5 minutes as the minus unit [2].

2.4.2 Traces

We use five traces downloaded from the Internet traffic Archive [43]: Clarknet-HTTP, NASA-HTTP, Saskatchewan-HTTP, UC Berkeley IP and WorldCup. The lengths of them range from 14 days to 30 days and all of trace files cover several peak requests. We have scaled the traces to meet our data center performance.

2.5 Results

In the section, we compare our optimization with other sub-optimal solutions to reflect our potential benefit in the experiments. For example, the aggressive server consolidation (ASTT = 5 minutes) could be considered as a typical case which prior works use to reduce electricity cost. Additionally, warmer cooling water might be a good example to demonstrate that prior works reduce cooling cost without the awareness of hardware maintenance cost.

2.5.1 The Optimization Based On Sweet Temperature

As illustrated in equation (16), when the server power is fixed, the total cost is only related to cooling and hardware maintenance. Figure 2-4 illustrates the impact of the inlet water temperature changing from 15°C to 35°C on the cooling cost and the cost of hardware maintenance of our data center with 30% utilization. These costs are normalized against the total costs when inlet water temperature is 15°C. Increasing inlet water temperature reduces cooling power especially when the temperature is below 25°C. However, high inlet water temperature increases the cost of hardware maintenance of CPU and memory. Observed from Figure 2-4, we can find an optimal inlet water temperature (25 °C in this case) which minimizes the total cost when utilization is fixed at 30%. In the following context, we will refer the sweet temperature to the optimal inlet water temperature. This observation justifies that high inlet water temperature is reasonable in data centers when the current average server utilization is low (below 30%). Otherwise, high inlet water temperature could hurt the cost of hardware maintenance during the high utilization.

Figure 2-5 shows the cooling and hardware maintenance costs of our data center when its utilization varies from 0% to 100%. The right vertical axis of the figure illustrates sweet temperatures for different utilizations. In the figure, the total costs for all utilizations are the lowest for the data center cooled by water at corresponding sweet temperatures. When the utilization of the data center is low, warm inlet water temperature offers more benefit since the cost of cooling power is larger than the cost of hardware maintenance (e.g. in our simulation result, the cost of cooling power is 1.65 times of the cost of hardware maintenance when the utilization is 10%). On the other hand, as the dat acenter utilization increases, we must keep a cold chilling water to cool down the heating hardware and slow the growth of hardware maintenance especially when their temperatures are close to the critical temperatures. Consequently, to minimize the total costs, inlet water temperature should be dynamically adjusted according to the data center utilization.

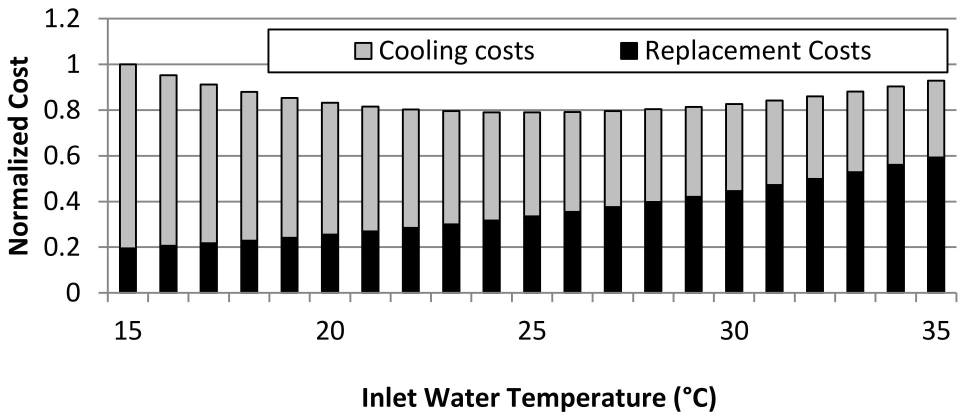

Figure 2-4. The impact of inlet water temperature on the costs of cooling power and hardware maintenance

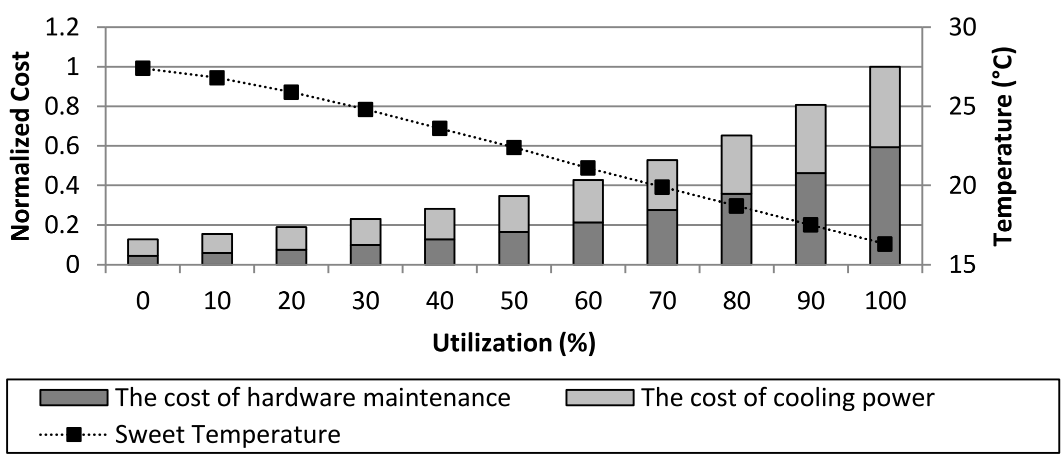

Figure 2-5. The variation of sweet temperature and these costs corresponding to the utilization of the data center

2.5.2 The Impact Of The Optimization Based On ASTT

The total cost by employing ASTT-P with different ASTT (ASTT from 5 to 80 minutes) is shown in Figure 2-6. The total costs of five traces with different ASTT are normalized against the total cost of five traces when ASTT is 5 minutes. Observed from this figure, the total cost of five traces can be reduced considerably when we select an optimal ASTT for them, though the best ASTT for five traces are not the same (around 30 minutes to 50 minutes) due to the small variation of the benefit of server consolidation(B_{sleeping}). In the following, we select 40 as the optimal ASTT for ASTT-P in the five traces. For ASTT-AR, we also obtained similar curves for five traces, though the optimal ASTT (around 60 minutes) of ASTT-AR for five trace is longer than that of ASTT-P due to the inaccurate prediction and the relatively slow growth of total cost. 60 minutes ASTT is selected as the optimal ASTT for ASTT-AR in the five traces for the following analysis.

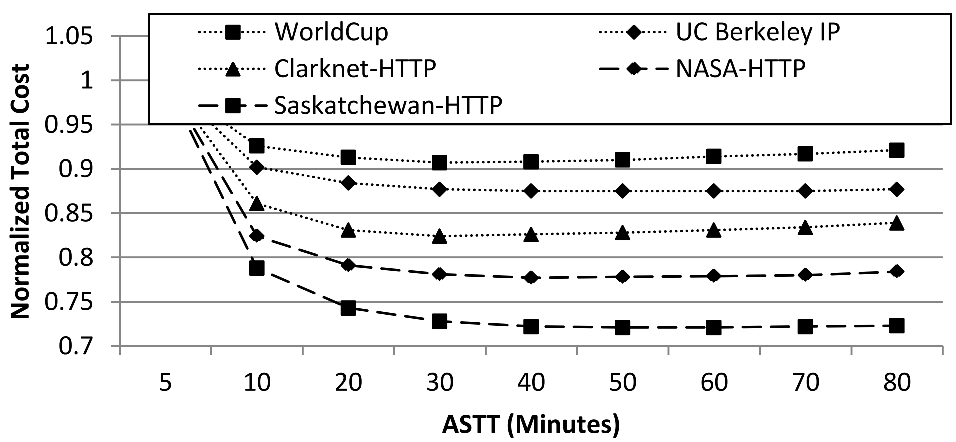

Figure 2-6. The normalized total cost reduced by ASTT-P when varying ASTT from 5 to 80 minutes in five traces

Figure 2-7 shows the comparison of the benefits of ASTT-P (ASTT = 40 minutes) and ASTT-AR (ASTT = 60 minutes) for five traces. All the total costs are normalized against the total cost of ASTT-P (ASTT = 5 minutes) in five traces respectively. ASTT-P offers the most benefit compared with ASTT-AR but requires an unreachable perfect prediction. As a practical algorithm, ASTT-AR still saves considerable cost while it guarantees the response time of 99% requests in the data center. To prove that the ASTT-AR can guarantee the QoS, Figure 2-8 shows the request success ratio which stands for the percentages of requests serviced under the constraint of the QoS. All the ratios are above 99% which satisfies our goal. To this purpose, ASTT-AR keeps more servers online than ASTT-P for the requests which are not caught by the prediction, losing slight performance benefit compared to ASTT-P.

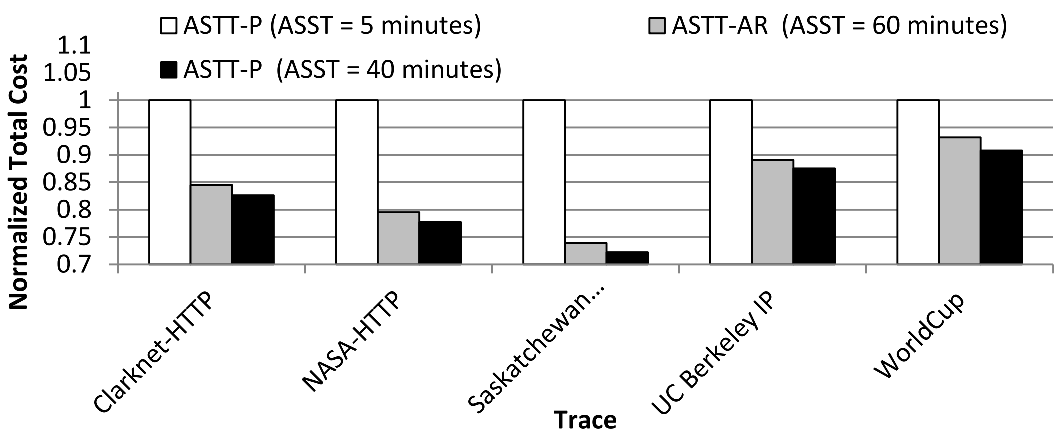

Figure 2-7. The total cost of ASTT-P with ASST (5 minutes), ASTT-AR with ASST (60 minutes), and ASTT-P with ASST-P with ASST (40 minutes) in five traces

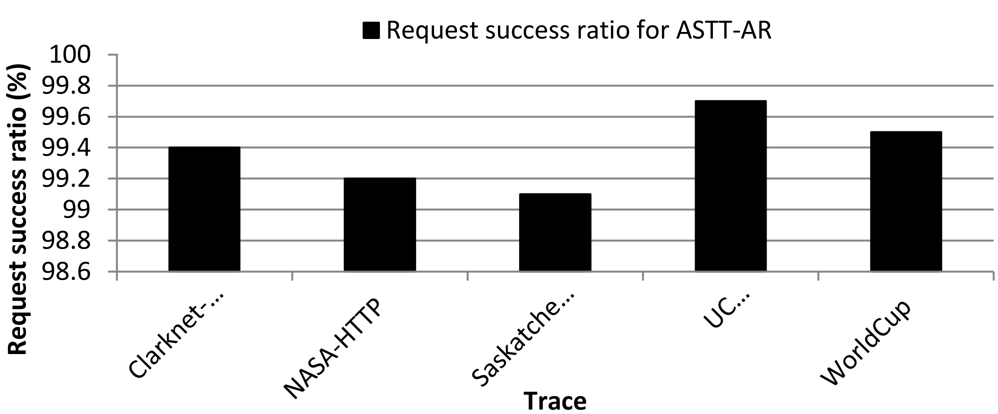

Figure 2-8. The request success ratio of ASTT-AR with ASST (60 minutes)

2.5.3 Joint Optimization Based On Sweet Temperature And ASTT-AR

Figure 2-9 shows the benefit when we combine dynamic optimal inlet water temperature (i.e. sweet temperature) and ASTT-AR for the five traces. The total costs of five traces are normalized against the total costs in five traces with ASTT-P (ASTT = 5 minutes and inlet water temperature fixed at 25 °C) as the baseline which represents a typical scheme. Overall, the total costs of sweet temperature and ASTT-AR offers 18% savings of total cost of five traces compared with the baseline in arithmetic mean based on our simulation results. Individually, ASTT-AR with inlet water temperature fixed at 25 °C yields 15% savings against the baseline, while ASTT-AR with sweet temperature yields extra 3% savings. The benefit of sweet temperature is relatively small compared to that of ASTT, since the hardware maintenance costs of CPU and DRAM is far less than the electricity cost of server power.

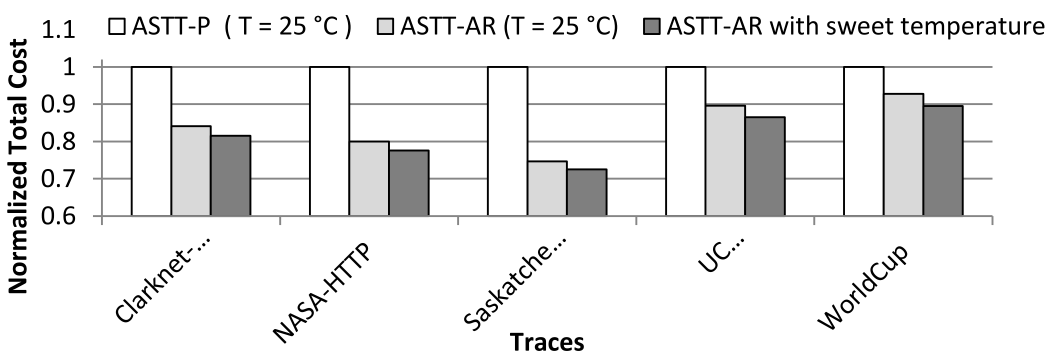

Figure 2-9. The total cost of ASTT-P with ASST (60 minutes) & fixed inlet water temperature (25 °c), ASTT-AR with ASST (60 minutes) & fixed inlet water temperature (25 °c), and ASTT-AR with ASST (60 minutes) & sweet temperature in five traces.

CHAPTER 3. OPTIMIZATION OF OPERATIONAL COSTS WITH RENEWABLE ENERGY

3.1 Renewable Energy

We integrate renewable energies into our model such as wind power and tidal power as a supplementary energy source of data centers. The integration leads to a comparison of cost savings between wind power and tidal power. Wind power exhibits moderate variability but high unpredictability, while tide power is relatively easily predicted but varies in wider range. Based on our evaluation, wind power is more profitable than tidal power due to its relatively low variability, since its less fluctuation provides more available power to the data center with larger overlaps between the wind power and the power consumption. This comparison can help operators of data centers to select a kind of renewable energy for their data centers.

3.1.1 Wind Power

Wind power is captured by wind turbines which converts kinetic energy into mechanical energy used to produce electricity. Figure 3-1 shows the output power of a typical wind turbine with respect to the wind speed [30]. The power is determined by three important wind speeds: cut-in wind speed, rated wind speed, and cut-off speed which are specific to a wind turbine. When the wind speed exceeds cut-in wind speed, the wind turbine starts to generate electricity. Its power grows as the wind speed increases, until it reaches the rated wind speed. The relation between the power and the wind speed could be shown in the equation: $\mathrm{P} = 0.5\mathrm{C_p}\ \emptyset \mathrm{A v^3}$, where$\mathrm{C_p}$ denotes the power efficiency, $\emptyset$ is the air density, A is the rotor swept area , and v is the wind speed. When the wind speed is between the cut-off wind speed and rated wind speed, the output power meets its maximum capacity. The power sharply drops to zero for protecting its blade assembly when the wind power exceeds the cut-off wind speed.

For most wind farm sites, the wind speed at most time is observed between the cut-in wind speed and the rated wind speed [30]. As a result, the output power is greatly sensitive to the wind speed due to their cubic relation. The resultant fluctuation of the power is shown in Figure 3-2 of the wind power trace used in our experiment. Although the average power demand derived from Saskatchewan-HTTP trace is approximate to the total wind power in the example, a considerable mismatch is expected due to their unrelated factors for their fluctuation: diary human activities and local weather condition. This mismatch leads to low wind power usage or requires a huge capacity of energy storage to reshape the wind power. However, the energy storage incurs additional capital costs and wastes wind energy, since required batteries are considerably expensive and waste energy due to energy conversions. When wind power is used as a supplementary energy resource for the data center, a conventional power grid also powers the data center unless its demand is less than wind power.

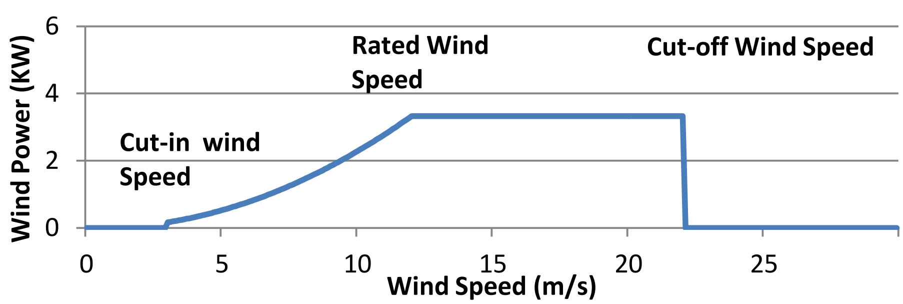

Figure 3-1. The relationship between wind speed and power

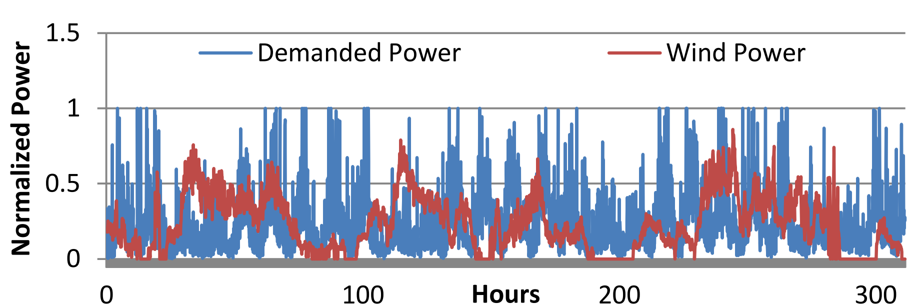

Figure 3-2. The mismatch between wind power and power consumption of data center

3.1.2 Tidal Power

Similar to wind power generated from the kinetic energy of air flow, tidal power is produced from a tidal stream of sea water which is relatively predictable due to a known tide table. This advantage potentially increases the usage of tidal power for data centers, since data centers have to reserve considerable energy for unpredictable wind power. It also lowers the capacity of energy storage in data centers which incurs noticeable capital cost, which further reduces the total cost for data centers. On the other hand, employing tidal power for data center is hindered by its considerable variance and pattern which is unrelated with human activities shown in Figure 3-3. They pose a serious challenge on boosting the usage of tidal power, since unbearable amount of energy storage is required to sync tidal power and demanded power from data centers. Alternatively, the usage of tidal power can be increased in the design: when tidal power surpasses demanded power, the exceeded power can be used to reduce hardware maintenance cost by maintaining lower temperature of cooling water and decreasing the number of server consolidation. Otherwise, the usage of tidal power is saturated since it is fully used by data centers.

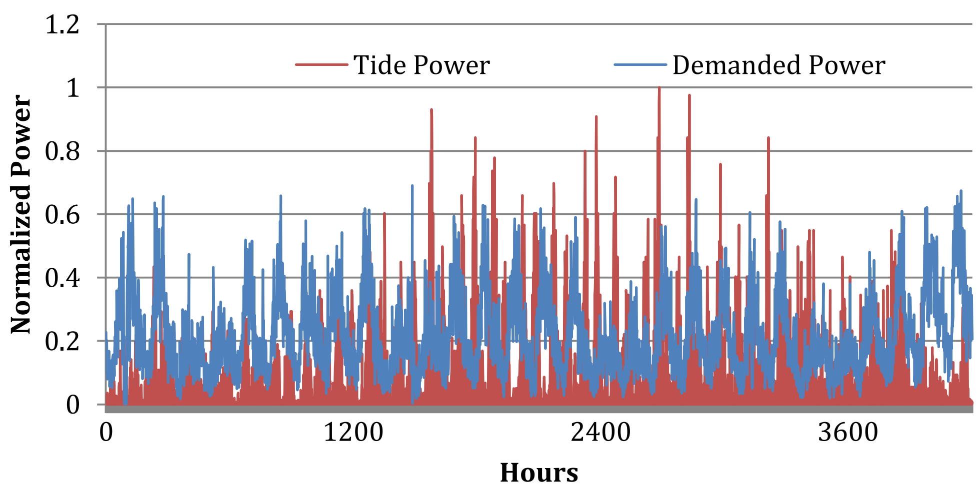

Figure 3-3. The mismatch between tide power and power consumption of data center

The power availability of a tidal stream with a tidal velocity V is estimated by using the equation: $P_{tide} = \frac{1}{2}pAV^3$, where p and A stand for water density and the area swept by rotor blades respectively [17]. The power generated from a tidal stream generator can be estimated by using the equation: $P_m = C_p P_{tide}$,where C_p represents the efficiency of conversion from kinetic energy into electrical energy [21].

3.2 Cost Optimization In Data Centers

3.2.1 Co-Optimization With Wind Power Or Tidal Power

For the unreliable renewable energies such as wind and tidal power, the proposed optimization is designed to increase its benefit. Rather than merely targeting at electricity costs, the optimization reduces the server maintenance costs at the expense of increased power consumption. The cost of such overhead could be avoided when the renewable power is larger than the electrical demand of data centers. It could be explained by the modified objective:

$$\begin{aligned} \min \{\mathrm{TC} = \sum_{n=1}^{ND} RC_{Disk} * [\mathrm{NAS}(t-1) - \mathrm{NAS}(t)]^{+} + \sum_{i=1}^{\mathrm{NAS}} \mathrm{RC}_{\mathrm{Server}}(i) \\ + K_{\$} * (P_{servers} + P_{cooling} + P_{PDL} - P_{Renewable})\} \end{aligned} \quad (21)$$

where $P_{Renewable}$ denote the renewable power at time t which can be wind power or tide power. There are two scenarios regarding to the comparison between the renewable power and the power demand of data centers:

- $P_{Renewable} \geq (P_{servers} + P_{cooling} + P_{PDL})$: Power Over Sufficient Period (POS period). With over sufficient renewable power, the only concern of this optimization is to reduce the cost of server maintenance costs by lowering the inlet water temperature and stopping turning off active servers. The power consumption of data centers could be increased as long as it is less than the renewable power.

- $P_{\text{Renewable}} < (P_{\text{servers}} + P_{\text{cooling}} + P_{\text{PDL}})$: Power Insufficient Period (PI period). When the renewable power partially compensates the power consumption of data centers, ASST-AR can reduce the electricity costs and server maintenance costs together by adjusting the inlet water temperature and the number of active servers. Since the derivative of the total cost in the factor of them is not affected by the renewable power, our method still reach the optimal point to minimize the total costs at each interval.

Disk replacement cost: Predicting the comparison between the renewable power and the power demand in the following intervals is substantial to reduce disk replacement costs by exploiting the benefit of the renewable power. The disk replacement cost is amortized over the saving of the electricity costs in the server sleeping time. The saving could be reduced if the sleeping time includes some POS periods. Consequently, the longer available sleeping time is demanded to compensate the disk replacement cost, since electricity saving can only be gained in the PI periods. The portion of POS periods in the following time become key to reduce disk replacement cost with the renewable power. To further reduce disk replacement cost, we design a POS predictor which is similar to the classical CPU branch predictor.

Wind Power ASST-AR: ASST-AR as well as sweet temperature is extended to fully exploit the benefit of the wind power based on the above discussion. The optimization of sweet temperature is intuitive; the inlet water temperature tracks the optimal value to balance the CPU and memory replacement costs in PI periods, otherwise, it is fixed at the lowest temperature to minimize the server maintenance cost. The modified ASST-AR also shows distinct policies in different periods to minimize the electricity cost and the replacement costs of disks shown in Figure 3-4. During POS periods, turning off active servers is prohibited to avoid incurred replacement cost; otherwise, the original ASST-AR still works. For capturing the immediately following POS period, we design a predictor based on the recent history, which is widely used in CPU branch prediction in Figure

3-4.The M is chosen to be 8, since we discovered that it is the optimal value for our five traces. This modified co-optimization is referred as Wind Power ASST-AR (WP-ASST-AR) which reduces electricity and server maintenance costs by utilizing the wind power.

```
//Predictor
If Renewable Power > power Consumption & Predictor <M
Predictor = Predictor + 1
If Renewable Power < power Consumption & Predictor >0
Predictor = Predictor – 1
//NAS : the Current Number of Active Servers
if NAS < FMRNAS [T]
NAS = FMRNAS [T]
Else
        // Turn off servers
        If  NAS > Max(FMRNAS [T,T+ ASTT])&& (Predictor<M/2)
        // Turn off(NAS - Max(FMRNAS [T,T+ ASTT])) servers
                NAS = Max(FMRNAS [T,T+ ASTT])
        Else
                pass
```

Figure 3-4. The algorithm of renewable power ASST-AR

Tidal Power ASST-AR**:** Sharing the same underlying idea, the co-optimization with tidal power known as TP-ASST-AR exploits the benefit of tidal power during POS periods. The benefit of the exploitation relies on how to accurately predict the length of a POS period in the following intervals, which can guide the algorithm to reduce unnecessary server consolidations and thus the total cost. In contrast with wind power, the prediction of tidal power is more accurate since it exhibits a relatively predictable pattern which is forecasted based on the predicted sea level in our experiment. On the other hand, demanded power is still unforeseeable and predicted based on its history as WP-ASST-AR.

3.3 Experiment Setup

We integrated the wind power model and the tidal power model into our simulations. We also calculated the wind power based on the relation between the wind speed and the output power of wind turbines [30], with the specific parameters such as power efficiency from [1]. The fourteen day wind speed trace is derived from [9]. We scale the average wind power to match the average power consumption for data centers for each trace. To scrutinize the benefit of our optimization, the average wind power is scaled to 50%, 75%, 100%, 125%, and 150% of the average power demand in each trace, which are referred as 50%, 75%, 100%, 125%, 150% Wind Power(WP). On the other hand, we derive a fourteen trace of tide power from [29]. Similarly, the average tidal power is scaled to the same portions of the average power, which are presented as 50%, 75%, 100%, 125%, 150% Tidal Power(TP). The extra power for data centers comes from the conventional power grid when the renewable power is less than the power demand.

3.4 Results

3.4.1 WP-ASST-AR

The benefit of WP-ASST-AR is revealed by the comparison between Figure 3-5 and Figure 3-6. Figure 3-5 shows the normalized costs in five traces of the simulated data center powered by 50%WP, 75%WP, and 100%WP, and 125%WP, and 150%WP with the baseline which merely targets electricity costs. The total costs are normalized against those of the baseline without the wind power. The shrinking marginal profit of increasing the wind power could be observed from that the total costs of 50%WP, 75%WP, 100%WP, 125%WP, and 150%WP are 0.77, 0.7, 0.66, 0.63, and 0.61 in geometric mean respectively. This trend is confirmed by the results of five traces. Figure 3-6 also shows this normalized costs but with WP-ASST-AR. The similar decrease of the marginal profit could be observed from that the total costs of 50%WP, 75%WP, 100%WP, 125%WP, and 150%WP are 0.67, 0.57, 0.51, 0.47, and 0.44 in geometric mean respectively. However, the benefit of WP-ASST-AR grows as the wind power increases based on the facts that with 50%WP, 75%WP, 100%WP, 125%WP, and 150%WP are 0.1, 0.13, 0.15, 0.16, and 0.17 compared with Figure 3-5.

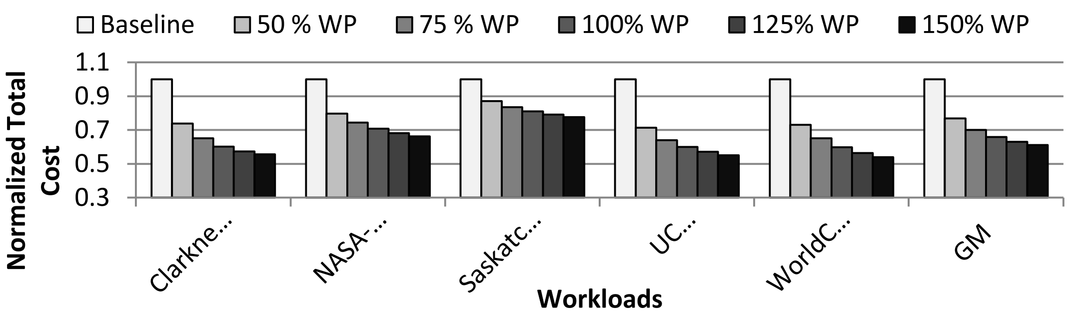

Figure 3-5. The normalized costs in five traces of the simulated data center powered by 50%WP, 75% WP, 100% WP, 125% WP, 150% WP

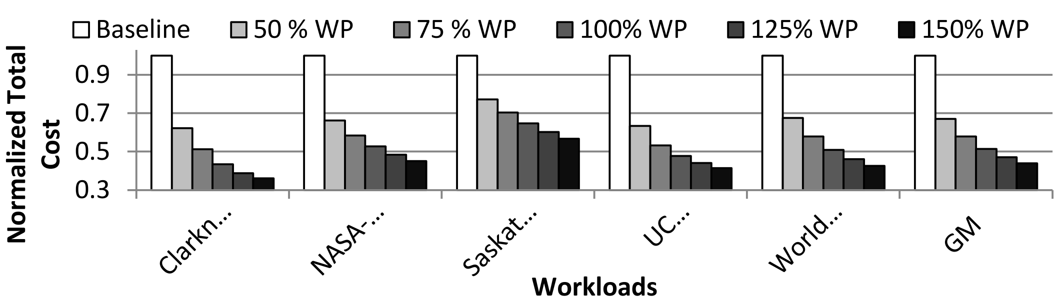

Figure 3-6. The normalized costs in five traces of the simulated data center powered by 50%WP, 75% WP, 100% WP, 125% WP, 150% WP, and optimized by WP-ASST-AR

Contributing the benefit of WP-ASST-AR, its higher cost savings of the wind power could be discovered by the comparison between Figure 3-7 and Figure 3-8. Figure 3-7 shows the total cost savings of the baseline yielded by 50%WP, 75%WP, and 100%WP, and 125%WP, and 150%WP. The increase of the savings shrinks as the wind power grows, and this trend is also perceived in Figure 3-8 showing the cost savings with WP-ASST-AR. More importantly, this cost saving is increased by WP-ASST-AR, which is consistent to the results of the total costs. The cost saving of the wind power increases from 22%, 29%, 31%, 35%, and 37% to 27%, 37%, 45%, 50% and 54% in geometric mean respectively. It implies that the more wind power are supplied, the more its cost saving could be obtained by WP-ASST-AR.

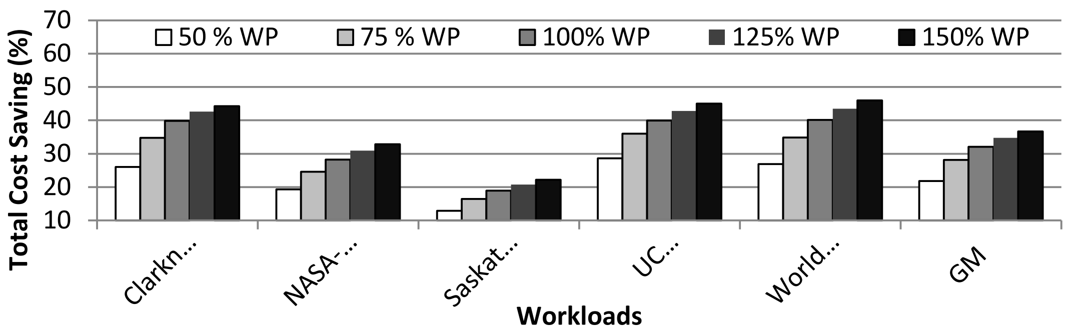

Figure 3-7. The total cost saving in five traces contributed by 50%WP, 75% WP, 100% WP, 125% WP, 150% WP

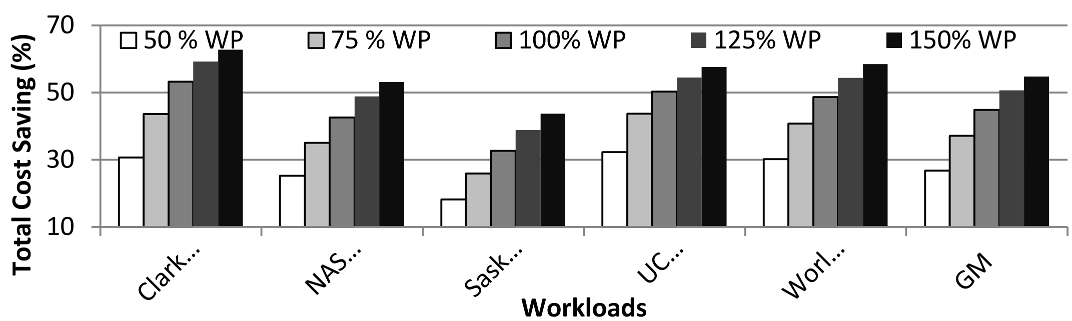

Figure 3-8. The total cost saving in five traces contributed by 50%WP, 75% WP, 100% WP, 125% WP, 150% WP with WP-ASST-AR

3.4.2 TP-ASST-AR

The total cost is reduced when the amount of tidal power is increased from 50% to 150% shown in Figure 3-9. Similar to wind power, the marginal benefit shrinks quickly and the total cost is steady when the amount of tidal power exceeds 125% demanded power. For example, the total cost of Sasktachewan-HTTP is only reduced by 25% total cost even if the average tidal power is 1.5 times the demanded power. It is caused by the larger variance of tidal energy shaped by the orbit of the Earth-Moon system. The low usage can be moderately mitigated by the TP-ASST-AR which aims at boosting the usage of tidal power shown in Figure 3-10. It yields a moderate benefit for all traces except Clarknet-HTTP which exhibits relatively large variance and leads to low accuracy of predicting subsequent power demand. Additionally, tidal power hardly provides long POS periods compared to wind power, since its frequent limited availability results from its noticeable variance. This drawback of tidal energy limits the benefit of TP-ASST-AR compared with WP-ASST-AR.

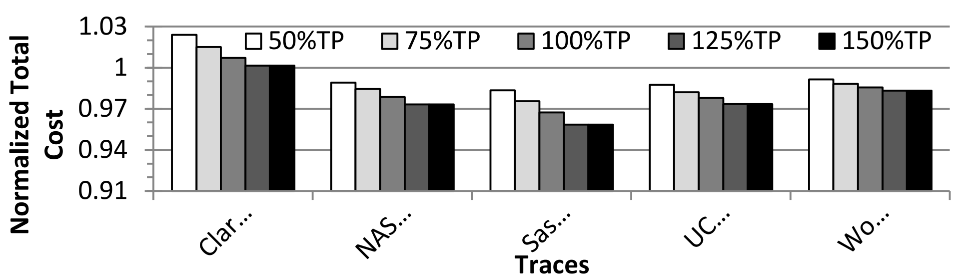

Figure 3-9. Reduced total cost normalized against the cost without TP-ASST-AR contributed by 50%TP, 75% TP, 100% TP, 125% TP, 150% TP

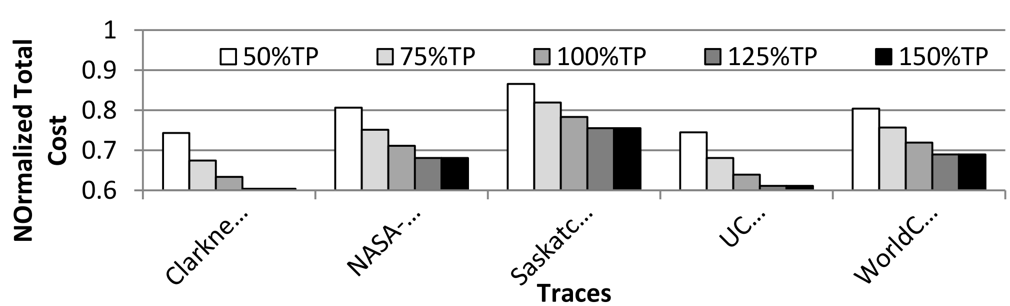

Figure 3-10. Total cost normalized against the cost without tidal energy contributed by 50%TP, 75% TP, 100% TP, 125% TP, 150% TP

CHAPTER 4. SUMMARY

The quick growth of electricity bill drives owners of data centers to employ server consolidation and the high temperature of data center However, the traditional air cooling system offers limited benefit of these two approaches due to its low energy efficiency of cooling power especially. We build a comprehensive framework which covers the costs of server power, cooling power, and hardware maintenance. Based on the models, we introduce a joint optimization of the costs of electricity and server maintenance. The approach gains 18% savings of the total cost and guarantees the response time of more than 99% requests. In the future, our framework will incorporate elaborated reliability models for state of the art servers and power managements which are also important for minimizing costs of data center owners.

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VITA

Shaoming Chen was born in 1985, in Wuhan, Hubei, China. He received his Bachelor of Engineering and Master of Engineering degrees in Electronics and Information Engineering from Huazhong University of Science and Technology, Wuhan, China, respectively in June 2008 and May 2012. Since then, he has been enrolled in the Department of Electrical and Computer Engineering at Louisiana State University, Baton Rouge, Louisiana, to pursue his doctorate degree. During this period, he passed his qualify exam in Fall 2012 and general exam in March 2015, respectively.