Making Scheduling "Cool": Temperature-Aware Workload Placement in Data Centers*

Justin Moore† Jeff Chase† Parthasarathy Ranganathan‡ Ratnesh Sharma‡

†*Department of Computer Science*
Duke University
{*justin,chase*}*@duke.edu*

‡*Internet Systems and Storage Lab*
Hewlett Packard Labs
{*partha.ranganathan, ratnesh.sharma*}*@hp.com*

Abstract

Trends towards consolidation and higher-density computing configurations make the problem of heat management one of the critical challenges in emerging data centers. Conventional approaches to addressing this problem have focused at the facilities level to develop new cooling technologies or optimize the delivery of cooling. In contrast to these approaches, our paper explores an alternate dimension to address this problem, namely a systems-level solution to control the heat generation through *temperature-aware workload placement*.

We first examine a theoretic thermodynamic formulation that uses information about steady state hot spots and cold spots in the data center and develop real-world scheduling algorithms. Based on the insights from these results, we develop an alternate approach. Our new approach leverages the non-intuitive observation that the source of cooling inefficiencies can often be in locations spatially uncorrelated with its manifested consequences; this enables additional energy savings. Overall, our results demonstrate up to a factor of two reduction in annual data center cooling costs over location-agnostic workload distribution, purely through software optimizations without the need for any costly capital investment.

1 Introduction

The last few years have seen a dramatic increase in the number, size, and uses of data centers. Large data centers contain up to tens of thousands of servers and support hundreds or thousands of users. For such data centers, in addition to traditional IT infrastructure issues, designers increasingly need to deal with issues of power consumption, heat dissipation, and cooling provisioning.

These issues, though traditionally the domain of facilities management, have become important to address at the IT level because of their implications on cost, reliability, and dynamic response to data center events. For example, the total cooling costs for large data centers (30,000 ft^2) can run into the tens of millions of dollars. Similarly, brownouts or cooling failures can lead to a reduced mean time between failure and service outages, as servers that overheat will automatically shut down. Furthermore, increases in server utilization [7, 16] or the failure of a CRAC unit can upset the current environment in a matter of minutes or even seconds, requiring rapid response strategies, often faster than what is possible at a facilities level. These conditions will accelerate as processor densities increase, administrators replace 1U servers with blades, and organizations consolidate multiple clusters into larger data centers.

Current work in the field of thermal management explores efficient methods of extracting heat from the data center [23, 27]. In contrast, our work explores *temperature-aware workload placement* algorithms. This approach focuses on scheduling workloads in a data center — and the resulting heat the servers generate — in a manner that minimizes the energy expended by the cooling infrastructure, leading to lower cooling costs and increased hardware reliability.

We develop temperature-aware workload placement algorithms and present the first comprehensive exploration of the benefits from these policies. Using simple methods of observing hot air flow within a data center, we formulate two workload placement policies: *zone-based discretization* (ZBD) and *minimize-heat-recirculation* (MINHR). These algorithms establish a prioritized list of servers within the data center, simplifying the task of applying these algorithms to real-work systems.

The first policy leverages a theoretic thermodynamic formulation based on steady-state hot spots and cold spots in

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the data center [27]. The second policy uses a new formulation based on the observation that often the measured effects of cooling inefficiencies are not located near the original source of the heat; in other words, heat may travel several meters through the data center before arriving at a temperature sensor. In both cases, our algorithms achieve the theoretical heat distribution recommendations, given discrete power states imposed by real-world constraints. We show how these algorithms can nearly halve cooling costs over the worst-case placement for a simple data center, and achieve an additional 18% in cooling savings beyond previous work. Based on these improvements we can eliminate more than 25% of the total cooling costs. Such savings in the 30,000 ft^2 data center mentioned earlier translate to a a $1 – $2 million annual cost reduction. Furthermore, our work is complementary to current approaches; given a fixed cooling configuration, we quantify the cost of adding load to specific servers. A data center owner can use these costs to maximize the utilization per Watt of their compute and cooling infrastructure.

The rest of this paper is organized as follows. Section 2 elaborates the motivation for this work and discusses the limitations of conventional facilities-only approaches. Section 3 describes the goals of temperature-aware workload placement and discusses the algorithms that we propose — ZBD and MINHR — as well as three baseline algorithms provided for comparison. Sections 4 and 5 present our results and discuss their implications. Section 6 concludes the paper.

2 Motivation

As yesterday's clusters grow into today's data centers, infrastructure traditionally maintained by a facilities management team — such as cooling and the room's power grid — are becoming an integral part of data center design. No longer can data center operators focus solely on IT-level performance considerations, such as selecting the appropriate interconnect fiber or amount of memory per node. They now need to additionally evaluate issues dealing with power consumption and heat extraction.

For example, current-generation 1U servers consume over 350 Watts at peak utilization, releasing much of this energy as heat; a standard 42U rack of such servers consumes over 8 kW. Barroso et al estimate that the power density of the Google data center is three to ten times that of typical commercial data centers [10]. Their data center uses commodity mid-range servers; that density is likely to be higher with newer, more power-hungry server choices. As data centers migrate to bladed servers over the next few years, these numbers could potentially increase to 55 kW per rack [21].

2.1 Thermal Management Benefits

A thermal management policy that considers facilities components, such as CRAC units and the physical layout of the data center, and temperature-aware IT components, can:

Decrease cooling costs. In a 30,000 ft^2 data center with 1000 standard computing racks, each consuming 10 kW, the initial cost of purchasing and installing the computer room air conditioning (CRAC) units is $2 – $5 million; with an average electricity cost of $100/MWhr, the annual costs for cooling alone are $4 – $8 million [23]. A data center that can run the same computational workload and cooling configuration, but maintain an ambient room temperature that is 5°C cooler, through intelligent thermal management can lower CRAC power consumption by 20% – 40% for a $1 – $3 million savings in annual cooling costs.

Increase hardware reliability. A recent study [28] indicated that in order to avoid thermal redlining, a typical server needs to have the air temperature at its front inlets be in the range of 20°C – 30°C. Every 10°C increase over 21°C decreases the reliability of long-term electronics by 50%. Other studies show that a 15°C rise increases hard disk drive failure rates by a factor of two [6, 13].

Decrease response times to transients and emergencies. Data center conditions can change rapidly. Sharp transient spikes in server utilization [7, 16] or the failure of a CRAC unit can upset the current environment in a matter of minutes or even seconds. With aggressive heat densities in the data center, such events can result in potentially disruptive downtimes due to the slow response times possible with the mechanical components at the facilities level.

Increase compaction and improve operational efficiencies. A high ratio of cooling power to compute power limits the compaction and consolidation possible in data centers, correspondingly increasing the management costs.

2.2 Existing Approaches

Data centers seek to provision the cooling adequately to extract the heat produced by servers, switches, and other hardware. Current approaches to data centers cooling provisioning are done at the facilities level. Typically, a data center operator will add the nameplate power ratings of all the servers in the data center — often with some additional slack for risk tolerance — and design a cooling infrastructure based on that number. This can lead to an excessive, inefficient cooling solution. This problem is exacerbated by the fact that the compute infrastructure in most data centers are provisioned for the peak (bursty) load requirement. It is estimated that typical operations of the data center often use only a fraction of the servers, leading to overall low server utilization [18]. The compounded overprovisioning of compute and cooling infrastructure drives up initial and recurring costs. For every Watt of power consumed by the compute infrastructure, a modern data center expends another one-half to one Watt to power the cooling infrastructure [23, 28].

In addition, the granularity of control provided in current cooling solutions makes it difficult to identify and eliminate the specific sources of cooling inefficiencies. Air flow within a data center is complex, nonintuitive, and easy to disrupt [23]. Changes to the heating system — servers and other hardware — or the CRAC units will take minutes to propagate through the room, complicating the process of characterizing air flow within the room.

Past work on data center thermal management falls into one of two categories. First, optimizing the flow of hot and cold air in the data center. Second, minimizing global power consumption and heat generation. The former approaches evaluate layout of the computing equipment in the data center to minimize air flow inefficiencies (e.g., hot aisles and cold aisles) [28] or design intelligent system controllers to improve cold air delivery [23]. The latter approaches focus on location-oblivious, global system power consumption (total heat load) through the use of global power management [12, 25], load balancing [11, 24], and power reduction features in individual servers [14].

2.3 Temperature-aware Workload Placement

However, these approaches do not address the potential benefits from controlling the workload (and hence heat placement) from the point of view of minimizing the cooling costs. Addressing thermal and power issues at the IT level — by incorporating temperature-related metrics in provisioning and assignment decisions — is complementary to existing solutions. The last few years have seen a push to treat energy as a first-class resource in hardware and operating system design, from low-power processors to OS schedulers [29, 31]. A facilities-aware IT component operates at a finer granularity than CRAC units. It can not only react to the heat servers generate, but control when and where the heat arrives. During normal operations, a temperature-aware IT component can maintain an efficient thermal profile within the data center, resulting in reduced annual cooling costs. In the event of a thermal emergency, IT-level actions include scaling back on server CPU utilization, scaling CPU voltages [14], migrating or shifting workload [22, 11], and performing a clean shutdown of selected servers.

Figure 1 presents an informal sketch to illustrate the potential of this approach. The cooling costs of a data center are plotted as a function of the data center utilization — increased utilization produces larger heat loads, resulting

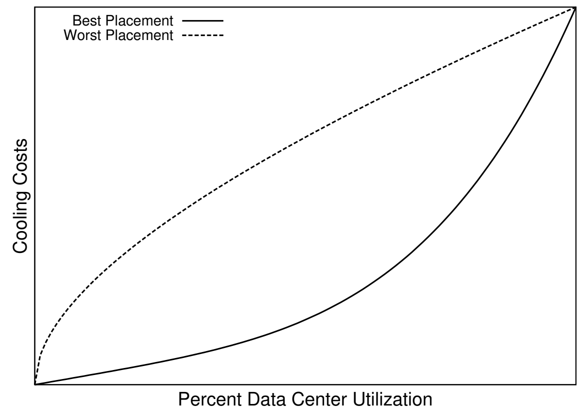


Figure 1: Approximate trends in cooling costs as a data center's utilization increases. Workload placement algorithms affect cooling costs by the assignment choices they make. At the extreme ends — all servers idle and all servers used — there are no choices. However, at all other times there exists a best and a worst workload placement strategy.

in higher cooling costs. At any given data center utilization, there is a best and worst workload placement strategy. The difference between the two lines indicate the potential benefits from our approach.

As Figure 1 indicates, the benefits of our approach are limited at the two end points — a data center at "0%" utilization or at "100%" utilization does not offer much scope for workload placement to reduce cooling costs. In the former, all servers are idle; in the latter, all servers are in use. In neither case do we have any choice in how to deploy workload. The benefits from temperature-aware workload placement exist at intermediate utilization levels when we can choose how we place our workload. Typical data centers do not maintain 100% utilization for extended periods of time, instead operating at mid-level utilizations where we can leverage temperature-aware workload placement algorithms [18].

The slope and "knee" of each curve is different for each data center, and reflects the quality of the physical layout of the data center. For example, a "best placement" curve with a knee at high utilization indicates a well laid-out data center with good air flow. However, given the inefficiencies resulting from the coarse granularity of control in pure facilities-based approach, we expect most data centers to exhibit a significant difference between the worst-case and best-case curves.

3 Workload Placement Policies

At a high level, the goals of any temperature-aware workload placement policy are to

- Prevent server inlet temperatures from crossing a pre-defined "safe" threshold.
- Maximize the temperature of the air the CRAC units pump into the data center, increasing their operating efficiency.

This section provides a brief overview of the thermodynamics of cooling, how intelligent workload placement reduces CRAC unit power consumption, and describes our placement policies.

3.1 Thermodynamics

The cooling cycle of a typical data center operates in the following way. CRAC units operate by extracting heat from the data center and pumping cold air into the room, usually through a pressurized floor plenum. The pressure forces the cold air upward through vented tiles, entering the room in front of the hardware. Fans draw the cold air inward and through the server; hot air exits through the rear of the server. The hot air rises — sometimes with the aid of fans and a ceiling plenum — and is sucked back to the CRAC units. The CRAC units force the hot air past pipes containing cold air or water. The heat from the returning air transfers through the pipes to the cold substance. The now-heated substance leaves the room and goes to a chiller, and CRAC fans force the now-cold air back into the floor plenum.

The efficiency of this cycle depends on several factors, including the conductive substance and the air flow velocity, but is quantified by a *Coefficient of Performance* (COP). The COP is the ratio of heat removed (Q) to the amount of work necessary (W) to remove that heat:

$$COP = \frac{Q}{W}$$
$$W = \frac{Q}{COP}$$

Therefore, the work necessary to remove heat is inversely proportional to the COP. A higher COP indicates a more efficient process, requiring less work to remove a constant amount of heat. For example, a cooling cycle with a COP of two will consume 50 kW to remove 100 kW of heat, whereas a cycle with a COP of five will consume 20 kW to remove 100 kW.

However, the COP for a cooling cycle is not constant, increasing with the temperature of the air the CRAC unit pushes into the plenum. We achieve cost savings by raising the plenum supply temperature, moving the CRAC units into a more efficient operating range. Figure 2 shows how the COP increases with higher supply temperatures for a typical water-chilled CRAC unit; this curve is from a water-chilled CRAC unit in the HP Utility Data Center. For example, if air returns to the CRAC unit at 20°C and we remove 10 kW of heat, cooling that air to 15°C, we expend 5.26 kW. However, if we raise the plenum supply temperature to 20°C, everything in the data center warms by 5°C. Cooling the same volume of air, now returning at 25°C, to 20°C removes the same 10 kW of heat, but only expends 3.23 kW. This is a power savings of almost 40%.

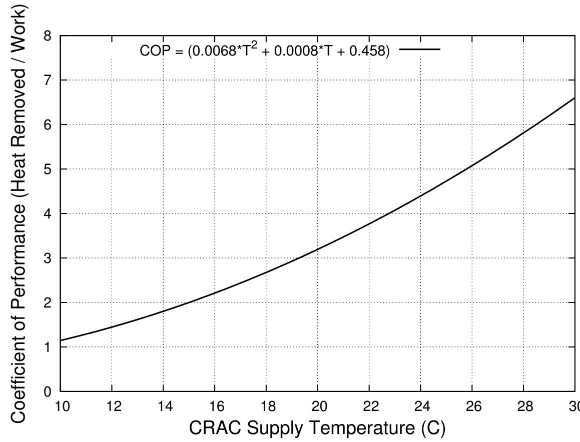


Figure 2: The Coefficient of Performance (COP) curve for the chilled-water CRAC units at the HP Labs Utility Data Center. As the target temperature of the air the CRAC pumps into the floor plenum increases, the COP increases, and the CRAC expends less energy to remove the same amount of heat.

Consequently, our scheduling policies attempt to maximize cooling efficiency by raising the maximum temperature of the air coming from the CRAC units and flowing into the plenum. Obviously, this has to be done in a manner that maintains prevents the server inlet temperatures from crossing their redlining thermal threshold.

3.2 Terminology

At a fundamental level, we categorize power allocation algorithms as either *analog* or *digital*. "Analog" algorithms specify per-server power budgets from the continuous range of real numbers [P_{off}, P_{max}]. While analog algorithms provide a detailed per-server budget, they are hard to implement in practice. It may be possible to meet these goals — a data center operator may deploy fine-grained load balancing in a web farm [8], utilize CPU voltage scaling [14], or leverage virtual machines [1, 9] for batch workloads — but in practice it is difficult to meet and maintain precise targets for power consumption.

"Digital" algorithms assign one of several pre-determined discrete power states to each server. They select which machines should be off, idle, or in use, particularly for workloads that fully utilize the processors. They could also leverage the detailed relationship between server utilization and power consumption to allow few discrete utilization states. Additionally, a *well-ordered* digital algorithm will create a list of servers sorted by their "desirability"; the list ordering is fixed for a given cooling configuration, but does not change for different data center utilization levels. Therefore, if data center utilization jumps from 50% to 60%, the servers selected for use at 50% are a proper subset of those selected at 60% utilization. Well-ordered algorithms simplify the process of integrating cooling-aware features with existing components such as SGE [4] or LSF [3], allowing us to use common mechanisms such as scheduling priorities. For example, SGE allows the administrator to define arbitrary "consumable" resources and simple formulas to force the scheduler to consider these resources when performing workload placement; modifying these resource settings is only necessary after a calibration run.

In this paper, we focus on algorithms that address the problem of discrete power states. We specifically focus on compute-intensive batch jobs such as multimedia rendering workloads, simulations, or distributed computation run for several hours [5]. These jobs tend to use all available CPU on a server, transforming the per-server power budgets available to a data center scheduler from a continuous range of [P_{off}, P_{max}] to a discrete set of power states: { $P_{off}, P_{idle}, P_1, \ldots, P_N$ }, where P_j is the power consumed by a server fully utilizing j CPUs. Additionally, they also provide sufficient time for the thermal conditions in the room to reach steady-state. If additional power states are considered, Section 5 discusses how our algorithms scale in a straightforward manner.

3.3 Baseline Algorithms

We use three reference algorithms as a basis for comparison.

UniformWorkload and CoolestInlets

The first algorithm is UNIFORMWORKLOAD, an "intuitive" analog algorithm that calculates the total power consumed by the data center and distributes it evenly to each of the servers. We chose this algorithm because, over time, an algorithm that places workload randomly will approach the behavior of UNIFORMWORKLOAD. Each server in our data center consumes 150 Watts when idle and 285 Watts when at peak utilization. Thus, a 40% UNIFORMWORKLOAD will place $((285-150)\cdot 0.40)+150 = 204$ Watts on each server.

The second baseline algorithm is COOLESTINLETS, a digital algorithm that sorts the list of unused servers by their inlet temperatures. This intuitive policy simply places workload on servers in the coldest part of the data center. Such an algorithm is trivial to deploy, given an instrumentation infrastructure that reports current server temperatures.

OnePassAnalog

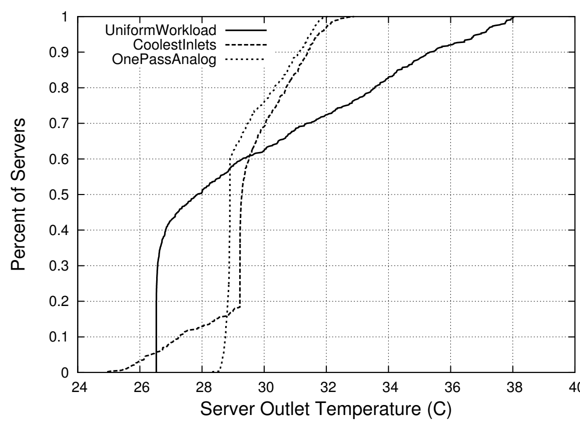


Figure 3: CDF of server exhaust temperatures for the three reference workload placement algorithms at 60% utilization. Both COOLESTINLETS and ONEPASSANALOG base workload placement decisions on data center conditions. However, ONEPASSANALOG has the least variance in server exhaust temperatures (4°C) leading to fewer heat buildups in the data center. Less variance allows us to raise CRAC supply temperatures further, increasing the COP, without causing thermal redlining.

The last policy is ONEPASSANALOG, an analog reprovisioning algorithm based on the theoretical thermodynamic formulation by Sharma et al [27], modified with the help of the original authors to allocate power on a per-server basis. The algorithm works by assigning power budgets in a way that attempts to create a uniform exhaust profile, avoiding the formation of any heat imbalances or "hot spots". A data center administrator runs one calibration phase, in which they place a uniform workload on each server and observe each server's inlet temperature. The administrator selects a reference { power, outlet temperature } tuple, { P_{ref}, T^{out}_{ref} }; this reference point can be one server, or the average server power consumption and outlet temperature within a row or throughout the data center. With this tuple, we calculate the power budget for each server:

$$P_i \quad = \quad \frac{T^{out}_{ref}}{T^{out}_i} \cdot P_{ref}$$

A server's power budget, P_i, is inversely proportional to its outlet temperature, T^{out}_i. Intuitively, we want to add heat to cool areas and remove it from warm areas.

It is important to note that ONEPASSANALOG responds to heat buildup by changing the power budget at the location of the observed increase. Intuitively, this is similar to other approaches — including the motherboard's thermal kill switch — in that it addresses the observed effect rather than the cause.

Figure 3 shows the CDF of server exhaust temperatures for the three reference workload placement algorithms in

```
ZoneBasedDiscretization(n, V, H, α) {
  while selected less than n servers {
    Get S_i, idle server with max power budget
    P_need = P_run − P_{S_i}
    Weight_Neighbors = α·size(V) + size(H)
    P_share = P_need / Weight_Neighbors
    Poach P_share from each of the H horizontal neighbors,
      (α · P_share) from each of the V vertical neighbors
  }
}
```

Figure 4: The core of the ZBD algorithm. n is the number of servers we want, V is the set of neighbors along the vertical axis, H is the set of neighbors along the horizontal axis, and α is the ratio of power borrowed per-vertical to power borrowed per-horizontal. P_{run} is the amount of power necessary to run one server at 100% utilization; P_{S_i} is the amount of power the OnePassAnalog algorithm allocates to server i. In general, $P_{run} \geq P_{S_i}$.

a data center at 60% utilization. A data center that employs OnePassAnalog scheduling has less variance in its server's exhaust temperatures; UniformWorkload and CoolestInlets have server exhaust temperatures that vary by as much as 9°C – 12°C, whereas OnePassAnalog varies by less than 4°C; this indicates fewer localized "hot spots" and heat imbalances.

3.4 Zone-Based Discretization (ZBD)

Our first approach is based on the theoretical formulation behind OnePassAnalog [27]. This formulation assigns heat inversely proportional to the server's inlet temperature. However, it suffers from the drawback that it is analog; it does not factor in the specific discrete power states of current servers: $\{ P_{idle}, \ldots, P_N \}$. Therefore, the challenge is to discretize the recommended analog distribution to the available discrete power states. Our research showed that conventional discretization approaches — ones that are agnostic to the notion of heat distribution and transfer — that simply minimize the absolute error, can result in worse cooling costs.

The key contribution of ZBD is that, in addition to minimizing the discretization error over the entire data center, it minimizes the differences between its power distribution and OnePassAnalog at coarse granularities, or geographic *zones*.

ZBD chooses servers by using the notions of proximity-based heat distributions and *poaching*. When selecting a server on which to place workload, the chosen server borrows, or "poaches" power from its zone of immediate neighbors whose power budget is not already committed. Within these two-dimensional zones, the heat produced by ZBD is similar to that produced by OnePassAnalog. Therefore, ZBD is an effective discretization of OnePassAnalog by explicitly capturing the underlying goal of OnePassAnalog: creating a uniform exhaust profile that reduces localized hot spots. A discretization approach that does not take this goal into account loses the benefits of OnePassAnalog.

Figure 4 describes the core of the ZBD discretization algorithm. ZBD allows us to define a variable-sized set of neighbors along the horizontal and vertical axes — H and V — and α, the ratio of power taken from the vertical to horizontal directions. These parameters enable us to mimic the physics of heat flow, as heat is more likely to rise than move horizontally. Consequently, "realistic" poaching runs set α larger than zero, borrowing more heavily vertically from servers in their rack.

Table 1 shows the operation of ZBD at a micro level, borrowing power from four vertical and two horizontal neighbors, giving the center server enough of a power budget to operate. The total amount of power and heat within the fifteen-server group remains the same, only shifted around slightly.

3.5 Minimizing Heat Recirculation (MinHR)

Our second approach is a new power provisioning policy that minimizes the amount of heat that recirculates within a data center: MinHR. Heat recirculation occurs for several reasons. For example, if there is not enough cold air coming up from the floor, a server fan can suck in air from other sources, usually hot air from over the top or around the side of racks. Similarly, if the air conditioning units do not pull the hot air back to the return vents or if there are obstructions to the air flow, hot air will mix with the incoming cold air supply. In all these cases, heat recirculation leads to increases in cooling energy.

Interestingly, some of these recirculation effects can lead to situations where the observed consequence of the inefficiency is spatially uncorrelated with its cause; in other words, the heat vented by one machine may travel several meters before arriving at the inlet of another server. We assert that an algorithm that minimizes hot air recirculation at the data center level will lead to lower cooling costs. Unlike ZBD, which reacts to inefficiencies by lowering the power budget at the site where heat recirculation is observed, MinHR focuses on the *cause* of inefficiencies. That is, it may not know how to lower the inlet temperature on a given server, but it will lower the total amount of heat that recirculates within the data center.

Therefore, unlike ZBD, we make no effort to create a uniform exhaust profile. The goals are to

- minimize the total amount heat that recirculates be-

184.61	216.77	207.15
184.44	216.80	207.41
186.24	216.88	207.66
189.25	216.86	207.82
193.41	216.82	207.89

(a) ONEPASSANALOG budgets.

184.61	*216.77*	207.15
184.44	*216.80*	207.41
186.24	**216.88**	*207.66*
189.25	*216.86*	207.82
193.41	*216.82*	207.89

(b) Select S_i and its *neighbors*. P_{need} = 68.12 Watts.

184.61	*203.67*	207.15
184.44	*203.70*	207.41
178.38	**285.00**	*199.80*
189.25	*203.76*	207.82
193.41	*203.72*	207.89

(c) Poach. P_{share} = 7.86 Watts, $(\alpha \cdot P_{share})$ = 13.10 Watts.

Table 1: The first iteration of ZBD with n = 6, size(H) = 2, size(V) = 4, and $\alpha = \frac{5}{3}$. The server with the highest power budget "poaches" power from its immediate neighbors. The total power allotted to these fifteen servers remains constant, but we now have a server with enough power to run at 100% utilization. At the end of this iteration, one server has enough power to run a full workload; after another $n-1$ iterations, we will have selected our n servers.

fore returning to the CRAC units.

- maximize the power budget — and therefore the potential utilization — of each server.

First, we need a way to quantify the amount of hot air coming from a server or a group of servers that recirculates within the data center. We define δQ as

$$\delta Q \quad = \quad \sum_{i=1}^{n} C_p \cdot m_i \cdot (T_i^{in} - T_{sup})$$

Here, n is the number of servers in the data center, C_p is the specific heat of air (a thermodynamic constant measured with units of $\frac{W \cdot sec}{kg \cdot K}$), m_i is the mass flow of air through server i in $\frac{kg}{sec}$, T_i^{in} is the inlet temperature for server i, and T_{sup} is the temperature of the cold air supplied by the CRAC units. In a data center with no heat recirculation — $\delta Q = 0$ — each T_i^{in} will equal T_{sup}.

Pod	$\Delta\delta Q_j$	HRF_j	$\frac{HRF_j}{SRF}$	$Power_j$	δQ_j
1	1000	2	0.050	250	125
2	400	5	0.125	625	125
3	250	8	0.200	1000	125
4	80	25	0.625	3125	125

Table 2: Hypothetical MINHR calibration results and workload distribution for a 40U rack of servers divided into four pods of 10 servers each. ΔQ_{ref} during calibration is 2 kW; the final workload is 5 kW.

Our workload placement algorithm will distribute power relative to the ratio of heat produced to heat recirculated:

$$P_i \quad \propto \quad \frac{Q_i}{\delta Q_i}$$

We run a two-phase experiment to obtain the heat recirculation data. This experiment requires an idle data center, but it is necessary to perform this calibration experiment once and only when there are significant changes to the hardware within the data center; for example, after the data center owner adds a new CRAC unit or adds new racks of servers. The first phase has the data center run a reference workload that generates a given amount of heat, Q_{ref}; we also measure δQ_{ref}, the amount of heat recirculating in the data center. For the sake of simplicity, our reference state has each server idle.

The second phase is a set of sequential experiments that measure the heat recirculation of groups of servers. We bin the servers into *pods*, where each pod contains s adjacent servers; pods do not overlap. We define pods instead of individual servers to minimize calibration time and to ensure that each calibration experiment generates enough heat to create a measurable effect on temperature sensors in the data center. In each experiment, we take the next pod, j, and maximize the CPU utilization of all its servers simultaneously, increasing the total data center power consumption and heat recirculation. After the new data center power load and resulting heat distribution stabilize, we measure the new amount of heat generated, Q_j, and heat recirculating, δQ_j. With these, we calculate the *Heat Recirculation Factor* (HRF) for that pod, where

$$\begin{aligned} HRF_j &= \frac{Q_j - Q_{ref}}{\delta Q_j - \delta Q_{ref}} \\ &= \frac{\Delta Q_j}{\Delta \delta Q_j} \end{aligned}$$

Once we have the ratio for each pod, we use them to distribute power within the data center. We sum the HRF

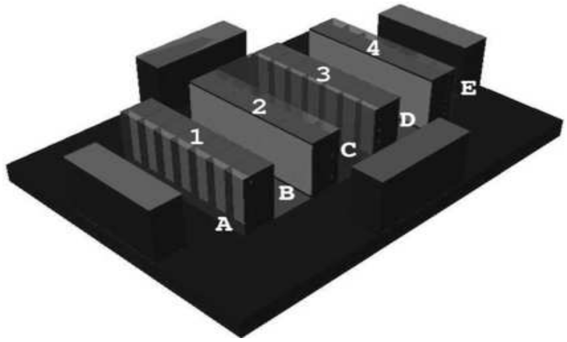


Figure 5: Layout of the data center. The data center contains 1120 servers in 28 racks, arranged in four rows of seven racks. The racks are arranged in a standard hot-aisle/cold-aisle configuration [28]. Four CRAC units push cold air into a floor plenum, which then enters the room through floor vents in aisles B and D. Servers eject hot air into aisles A, C, and E.

from each pod to get the *Summed Recirculation Factor* (SRF). To calculate the per-pod power distributions, we simply multiply the total power load by that pod's HRF, divided by the SRF. This power budget distribution satisfies both of our stated goals; we maximize the power budget of each pod — maximizing the number of pods with enough power to run a workload — while minimizing the total heat recirculation within the data center. With this power distribution, each pod will recirculate the same amount of heat.

As before, we need to discretize the analog recommendations based on the HRF values for the power states in the servers. The scheduler then allocates workloads based on the discretized distribution. Note that the computed HRF is a property of the data center and is independent of load.

Table 2 shows an example of MINHR for a 40U rack of 1U servers divided into four pods. The resulting power budgets leads to identical amounts of heat from each pod recirculating within the data center. Although we could budget more power for the bottom pod to further minimize heat recirculation, but that would reduce the power budgets for other pods and lessen the number of available servers. Additionally, it is likely that the bottom pod has enough power to run all 10 servers at 100% utilization; increasing its budget serves no purpose, and instead reduces the amount of power available to other servers.

4 Results

This section presents the cooling costs associated with each workload placement algorithm.

4.1 Data Center Model

Given the difficulties of running our experiments on a large, available data center, we used Flovent [2], a Computational Fluid Dynamics (CFD) simulator, to model workload placement algorithms and cooling costs of the medium-sized data center shown in Figure 5. This methodology has been validated in prior studies [27].

The data center contains four rows with seven 40U racks each, for a total of 28 racks containing 1120 servers. The data center has alternating "hot" and "cold" aisles. The cold aisles, B and D, have vented floor tiles that direct cold air upward towards the server inlets. The servers eject hot air into the remaining aisles: A, C, and E. The data center also contains four CRAC units, each having the COP curve depicted in Figure 2. Each CRAC pushes air chilled to 15°C into the plenum at a rate of 10,000 $\frac{ft^3}{min}$. The CRAC fans consume 10 kW each.

The servers are HP Proliant DL360 G3s; each 1U DL360 has a measured power consumption of 150W when idle and 285W with both CPUs at 100% utilization. The total power consumed and heat generated by the data center is 168 kW while idle and 319.2 kW at full utilization. Percent utilization is measured as the number of machines that are running a workload. For example, when 672 of the 1120 servers are using both their CPUs at 100% and the other 448 are idle, the data center is at 60% utilization. To save time configuring each simulation, we modeled each pair of DL360s as a 2U server that consumed 300W while idle and 570W while at 100% utilization.

Calculating Cooling Costs

At the conclusion of each simulation, Flovent provides the inlet and exhaust temperature for each object in the data center. We calculate the cooling costs for each run based on a maximum safe server inlet temperature, T^{in}_{safe}, of 25°C, and the maximum observed server inlet temperature, T^{in}_{max}. We adjust the CRAC supply temperature, T_{sup}, by T_{adj}, where

$$T_{adj} \quad = \quad T^{in}_{safe} - T^{in}_{max}$$

If T_{adj} is negative, it indicates that a server inlet exceeds our maximum safe temperature. In response, we need to lower T_{sup} to bring the servers back below the system redline level.

Our cooling costs can be calculated as

$$C \quad = \quad \frac{Q}{COP(T = T_{sup} + T_{adj})} + P_{fan}$$

where Q is the amount of power the servers consume, $COP(T = T_{sup} + T_{adj})$ is our COP at $T_{sup} + T_{adj}$,

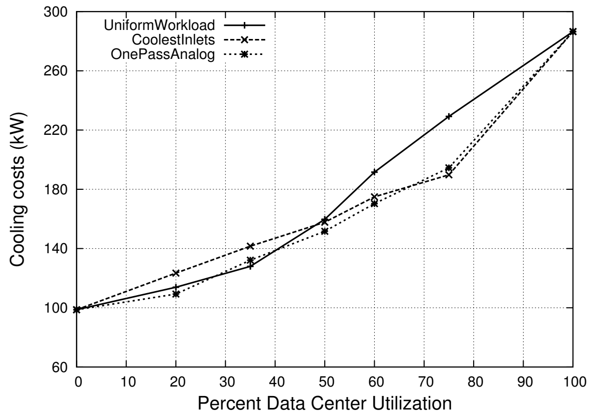


Figure 6: ONEPASSANALOG is consistently low, indicating a potential "best" cooling curve described in Figure 1. UNIFORMWORKLOAD performs well at low utilizations, but lacks the ability to react to changing conditions at higher utilizations. COOLESTINLETS performs well at higher utilizations, but is more expensive at low-range and mid-range utilization.

calculated from the curve in Figure 2, and P_{fan} is the total power consumed by the CRAC fans. Currently we assume a uniform T_{sup} from each CRAC due to the complications introduced by non-uniform cold air supply; we discuss these complications, proposed solutions, and ongoing work in Section 5.

4.2 Baseline Algorithms

Figure 6 shows the cooling costs for our three baseline algorithms. UNIFORMWORKLOAD performs well at low utilization by not placing excessive workload on servers that it shouldn't. At high utilization, though, it places workload on all servers, regardless of the effect on cooling costs. In contrast, we see that ONEPASSANALOG performs well both at high and low data center utilization. It reacts well as utilization increases, scaling back the power budget on servers whose inlet temperatures increase. This avoids creating hot spots in difficult-to-cool portions of the room that would otherwise cause the CRAC units to operate less efficiently. COOLESTINLETS does well at high and mid-range utilization for this data center, but is about 10% more expensive than ONEPASSANALOG at low and moderate utilization.

4.3 ZBD

Parameter Selection

For ZBD to mimic the behavior of ONEPASSANALOG, we need to select parameters that reflect the underlying heat flow. Heat rises, so we set our α to be greater than 1, and our vertical neighborhood to be larger than our horizontal neighborhood. Our simulated servers are 2U high; therefore our servers are 8.89cm (3.5in) tall and 60.96cm (24in) wide. Since heat intensity is inversely proportional to the square of the distance from the source, it makes little sense to poach two servers or more (greater than one meter) in either horizontal direction. Noting that our rows are 20 servers high and 7 across, we maintain this ratio both in poaching distance and poaching ratio. We set our vertical neighborhood to be three servers in either direction, and our α to $\frac{20}{7}$. These parameters are simple approximations; in section 5 we discuss methods of improving upon ZBD parameter selection.

Zone Size	Avg Power	UW CoV	ZBD CoV
2U	462	0.009	0.008
4U	924	0.012	0.009
8U	1848	0.018	0.006
10U	2310	0.020	0.006

Table 3: Coefficient of variance (CoV) of differences in zonal power budgets between ONEPASSANALOG and the UNIFORMWORKLOAD (UW) and the ZBD algorithms at 60% utilization. Small coefficients indicate a distribution that mimics ONEPASSANALOG closely, creating a similar exhaust profile.

Results

The next question is whether we met our goals of matching the high-level power allocation behavior of ONEPASSANALOG. In order to quantify the similarity of any two algorithms' power distributions, we break each 40U rack into successively larger zones; zones are adjacent and do not overlap. We sum the servers' power allocations to get that zone's budget. Table 3 shows the per-pod variance between the ONEPASSANALOG zone budgets those of UNIFORMWORKLOAD and ZBD power distributions are to the ONEPASSANALOG power budgets at different granularities. Unsurprisingly, UNIFORMWORKLOAD has the largest variance at any zone size; it continues to allocate power to each server, regardless of room conditions. However, ZBD closely mirrors the power distribution budgeted by ONEPASSANALOG.

Figure 7 shows the relative costs of ZBD against our three baseline algorithms as we ramp up data center utilization. Like ONEPASSANALOG, ZBD performs well both at low and high utilizations. Most importantly, we see that ZBD mimics the behavior and resulting cooling costs of ONEPASSANALOG within two percent. Even with intuitive parameter selection and the challenge of discretizing the analog distribution, we met or exceeded the savings available using the theoretical best workload assignment algorithm from previously published work.

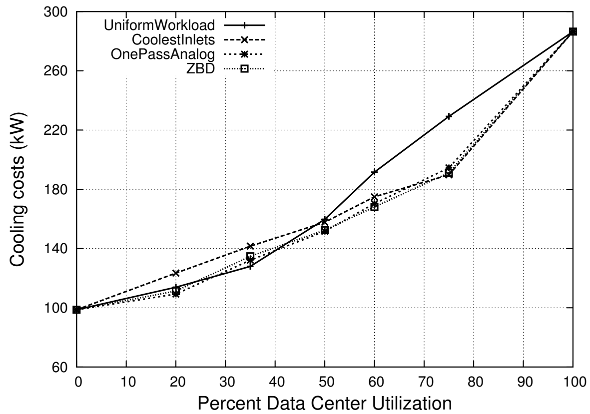


Figure 7: ZBD compared to our baseline algorithms. ZBD also works well at high and low utilizations, staying within $\pm$ 3% of ONEPASSANALOG.

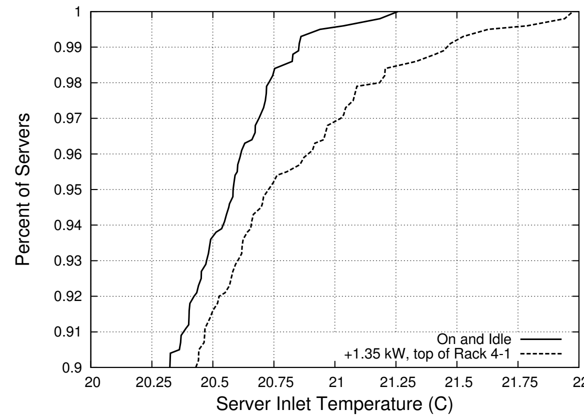


Figure 8: CDF of the warmest ten percent of server inlets for the MINHR phase-one calibration workload, and after adding a total of 1.35 kW to ten servers during a phase-two recirculation workload. A 1°C increase in the maximum server inlet temperature results in 10% higher cooling costs. This phase-two workload was at the top corner of row 4.

4.4 MinHR

Calibration

The performance of MINHR depends on the accuracy of our calibration experiments. Our goals in selecting calibration parameters for MINHR, such as pod sizes and our Q_{ref}, were to allow for a reasonable calibration time and a reasonable degree of accuracy. If pod sizes are too small, we may have too many pods and an unreasonably long real-world calibration time — approximately twenty minutes per pod — and the $\Delta\delta Q_i$ may to too small to create any observable change. Since calibration times using Flovent are significantly longer than in real life — one to two hours per pod — we chose a pod size of 10U. This translates to a 1.35 kW ΔQ_i, as we increase each server from 150W to 285W. While smaller pods may give us data at a finer granularity, the magnitude of δQ may be too small to give us an accurate picture of how that pod's heat affects the data center.

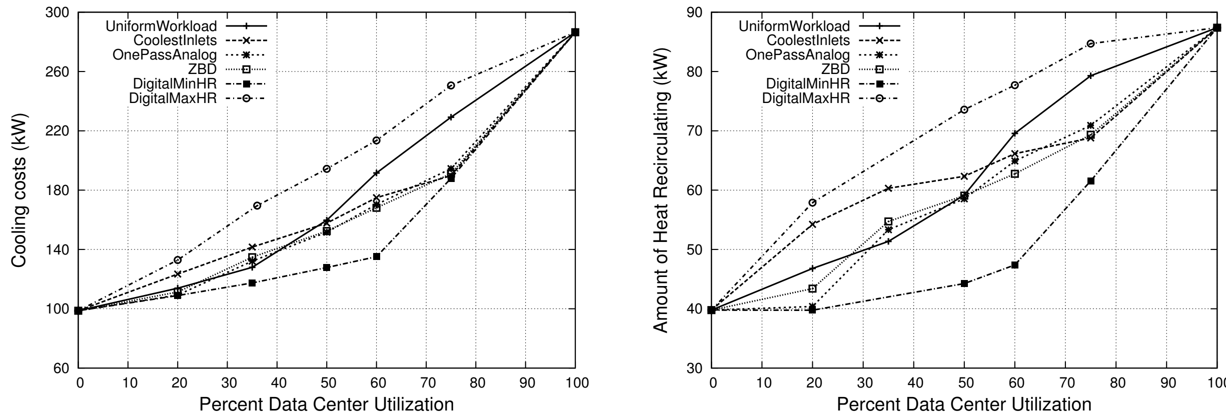
Figure 8 demonstrates the importance of locating the sources of heat recirculation. It shows the warmest 10% of server inlets for our calibration phase and for the recirculation workload at the top pod of a rack on the end of row 4. Even though we increase the total power consumption of the servers by only 0.80% (1.35 kW), the cooling costs increase by 7.56%. A large portion of the hot exhaust from these servers does not return to a CRAC unit, instead returning to the servers. Inlets at the top of row 4 increase by over 1°C, and servers at the same end of row 3 see an increase in inlet temperature of over $\frac{2}{3}$°C.

With MINHR, unlike ONEPASSANALOG, it was not necessary to perform any form discretization on the analog power budgets from. Figure 9 shows the CDF of server power budgets while our data center is at 60% utilization. In ONEPASSANALOG, of the 1120 servers, only 84 fall outside the operating range of our DL360s, thus necessitating the use of ZBD.

However, MINHR assigns power budgets between 13 and 3876 Watts per 1U server, with only 160 falling within the operating range; we chose simply to sort the servers by their power budget and chose the X% with the highest budgets, where X is our target utilization. We define ANALOGMINHR as the original, unrealistic power distribution, and the sort-and-choose as DIGITALMINHR. For the sake of clarity, we define DIGITALMAXHR as DIGITALMINHR in reverse; we start at the bottom of the list, using the worst candidates and moving up.

Results

Figure 10(a) compares our four previous algorithms against DIGITALMINHR and DIGITALMAXHR. At midrange utilization, DIGITALMINHR saves 20% over ONEPASSANALOG, 30% over UNIFORMWORKLOAD, and nearly 40% over DIGITALMAXHR. The costs of each algorithm are related to the heat recirculation behaviors they cause. At low utilization, DIGITALMAXHR quickly chooses servers whose exhaust recirculates extensively, whereas DIGITALMINHR does not save much over ONEPASSANALOG; this indicates that initially ONEPASSANALOG also minimizes heat recirculation. As utilization increases, however, all algorithms except DIGITALMINHR end up placing load on servers that recirculate large amounts of heat; DIGITALMINHR knows exactly which servers to avoid. At near-peak utilizations, however, DIGITALMINHR has run out of "good" servers to use, driving up cooling costs.



(a) Cooling costs for our baseline algorithms, ZBD, and best and worst heat-recirculation-based algorithms.

(b) The amount of heat recirculating. Note that the increase in heat recirculation closely mirrors the increase in cooling costs.

Figure 10: At mid-range utilizations, DIGITALMINHR costs 20% less than ONEPASSANALOG, 30% less than UNIFORMWORKLOAD and almost 40% less than the worst possible workload distribution.

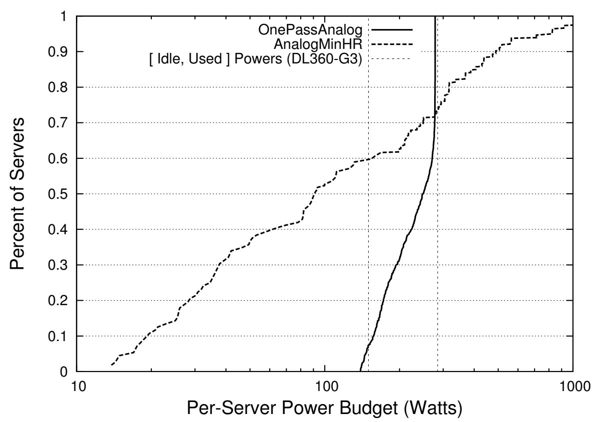


Figure 9: CDF of ONEPASSANALOG and ANALOGMINHR budgets at 60% utilization. ONEPASSANALOG budgets fall within the DL360's operating range; this facilitates ZBD's zone-based discretization. The minimum and maximum ANALOGMINHR budgets are more than an order of magnitude outside this range, eliminating the need for or effectiveness of any discretization algorithm.

Figure 10(b) graphs δQ for each algorithm. DIGITALMINHR achieves its goal, minimizing recirculation and cooling costs until there are no "good" servers available. Conversely, DIGITALMAXHR immediately chooses "bad" servers, increasing power consumption by 30.2 kW and heat recirculation by 18.1 kW. Note that cooling costs are closely related to the amount of heat recirculating within the data center.

4.5 ZBD and MinHR Comparison

At a glance, DIGITALMINHR provides significant savings over all other workload placement algorithms. It directly addresses the cause of data center cooling inefficiencies, and is constrained only by the physical air flow design of the data center. Unfortunately, the calibration phase is significantly longer than the one ZBD requires. A real-world calibration of our model data center would take 56 hours; this is not unreasonable, as the entire calibration run would complete between Friday evening and Monday morning. However, a calibration run is necessary whenever the physical layout of the room changes, or after a hardware or cooling upgrade. Conversely, ZBD is consistent and the best "reactive" digital algorithm. It only requires one calibration experiment; for our data center, this experiment would complete within a half-hour.

Ultimately, the data center owner must decide between long calibration times and savings in cooling costs. If the cooling configuration or physical layout of the data center will not change often, then a MINHR-based workload placement strategy yields significant savings.

5 Discussion

Additional Power States

Our previous experiment assumes the computer infrastructure only had two power states: idle and used. However, many data center management infrastructure components — such as networked power switches, blade control planes, and Wake-On-LAN-enabled Ethernet cards — al-

# Off	Power (kW)	Cooling (kW)	% Savings
56	273.0	156.9	16.54
112	264.6	142.9	23.96
168	256.2	134.4	28.51
224	247.8	**126.00**	**32.96**

Table 4: We leverage MINHR's sorted list of server "desirability" to select servers to turn off during 75% utilization. We reduce the power consumed by the computer infrastructure by 12%, yet reduce cooling costs by nearly one-third.

low us to consider "off" as another power state. Both the algorithms can leverage additional power states to allow them to more closely match the analog power budgets.

To demonstrate the potential for increased improvements, we focus on some experiments using the best algorithm from the last section. DIGITALMINHR's per-pod HRF values allow us to sort servers by heat recirculation and power down or fully turn off the "worst" servers. Table 4 presents the results of turning 5, 10, and 15% of the "worst" servers off during 75% utilization while using the DIGITALMINHR placement algorithm. Initially the computer infrastructure was consuming 281.4 kW, and expending 187.9 kW to remove this heat. Turning off only 56 servers, 8.4 kW of compute power, reduces cooling costs by nearly one-sixth. MINHR with an "off' option reduces cooling costs by nearly another third by turning off 20% of the servers.

When compared to the savings achieved by ONEPASSANALOG over UNIFORMWORKLOAD, this approach represents a factor of three increase in those cooling savings, reducing UNIFORMWORKLOAD cooling costs by nearly 60%. These long-term savings may be reduced, however, by the decreased hardware reliability caused by power-cycling servers.

How far to perfection?

In this section, we compare our results to the absolute theoretical minimum cost of heat removal, as defined by physics. It is possible to calculate the absolute minimum cooling costs possible, given the COP curve of our CRAC units. Assume we formulate the perfect workload placement algorithm, one that eliminates hot air recirculation. In that case, we have the situation described in Section 3.5: CRAC supply temperatures equal the maximum safe server inlet temperatures. Plugging the data from the COP curve in figure 2, we obtain $W_{optimal} = \frac{Q}{4.728}$.

Figure 11 compares all our workload placement algorithms against the absolute minimum costs, as governed by the above equation. It should be noted that the absolute minimum represents a realistically unobtainable point as is evident from the benefits it can obtain even at the 100%

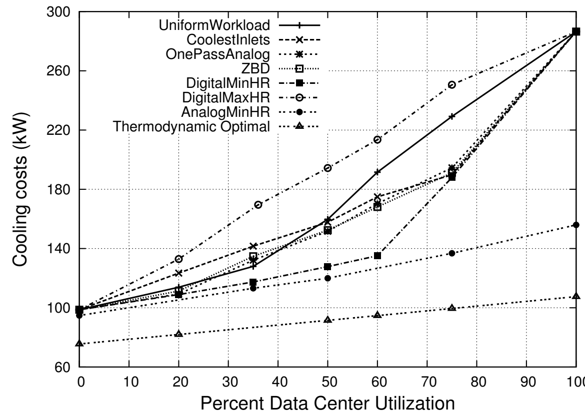


Figure 11: Cooling costs for all workload placement algorithms, ANALOGMINHR, and the absolute minimum costs for our data center.

data point where there is no slack in workload placement. However, in spite of this, for our simple data center at mid-range workloads, DIGITALMINHR achieves over half the possible savings as compared to UNIFORMWORKLOAD. These savings are through changes a data center administrator can make entirely at the IT level in software, such as modifying a batch queue or other server assignment scheduler. Furthermore, as discussed earlier, these changes are complementary to other facilities approaches, including improved rack locations and cooling configurations.

Instrumentation and Dynamic Control

The work discussed in this paper assumes an instrumentation infrastructure in the data center such as Splice [19] that provides current temperature and power readings to our algorithms. Related work in the data instrumentation space includes PIER [15], Ganglia [26] and Astrolabe [30]. Additionally, algorithms such as ONEPASSANALOG, ZBD, and MINHR include calibration phases based on past history. These phases could potentially be sped by systematic thermal profile evaluations through a synthetic workload generation tool such as `sstress` [20]. A moderately-sized data center of 1000 nodes will take about two days to calibrate fully. At the end of the calibration phase, however, which we will have the power budgets for that data center. These budgets are constant unless the cooling or computational configuration changes, such as by adding or removing servers.

Further, the work discussed in this paper pertains to static workload assignment in a batch scheduler to reduce cooling costs from a heat distribution perspective. We assume that the cooling configuration is not being optimized concurrently; in other words, CRAC units may not vary their supply temperatures individually, or change their fan speeds at all. However, some data centers exist where aggressive cooling optimizations could concurrently vary the cooling configurations.

For these scenarios, we are currently exploring the possibility of using system identification techniques from control theory [17] to "learn" how the thermal profile of the data center changes as cooling settings change. These identification tools will reveal the relationships between cooling parameters and heat recirculation observations, allowing us to expand the uses of temperature-aware workload placement to include such features as emergency actions in the event of CRAC unit failure. For the time being, however, a data center owner could perform one calibration phase with each CRAC unit off to simulate the failure of that unit and obtain the relative power budgets and server ordering.

6 Conclusion

Cooling and heat management are fast becoming the key limiters for emerging data center environments. As data centers grow during the foreseeable future, we must expand our understanding of cooling technology and how to apply this knowledge to data center design from an IT perspective. In this paper, we explore temperature-aware resource provisioning to control heat placement from a systems perspective to reduce cooling costs.

We explore the physics of heat transfer, and present methods for integrating it into batch schedulers. To capture the complex thermodynamic behavior in the data center, we use simple heuristics that use information from steady-state temperature distribution and simple cause-effect experiments to calibrate sources of inefficiencies. To capture the constraints imposed by real-world discrete power states, we propose location-aware discretization heuristics that capture the notion of zonal heat distribution, as well as recirculation-based placement. Our results show that these algorithms can be very effective in reducing cooling costs. Our best algorithm nearly halves cooling costs when compared to the worst-case scenario, and represents a 165% increase in the savings available through previously published methods. All these savings are obtained purely in software without any additional capital costs. Furthermore, our results show that these improvements can be larger with more aggressive use of power states, as is likely in future systems.

Though we focus mainly on cooling costs in this paper, our algorithms can also be applied to other scenarios such as graceful degradation under thermal emergencies. In these cases, compared to longer timescales associated with the more mechanical-driven facilities control, temperature-aware workload placement can significantly improve the response to failures and emergencies. Similarly, the principles underlying our heuristics can be leveraged in the context of more complex dynamic control algorithms as well.

In summary, as future data centers evolve to include ever larger number of servers operating in increasingly denser configurations, it will become critical to have heat management solutions that go beyond conventional cooling optimizations at the facilities level. We believe that approaches like ours that straddle the facilities and systems management boundaries to holistically optimize for power, heat, and cooling, will be an integral part of future data center solutions to address these challenges.

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