Development of a Global Data Center Infrastructure Systems Model bound by the System's End to End Life Cycle

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0.1 Abstract

Data centers (DCs) are critical for modern society. They house information technology (IT) hardware and store data for financial institutions, social media accounts, entertainment portals, and virtual meeting forums amongst many other things. In their physical embodiment, networks of DCs are global scale systems. Within these systems, each DC's size can be as large as a college campus and consume 100 times the amount of electrical energy every hour as residential facilities do in a day. Given their growing demand, it is extremely important to develop a global level modeling framework to help make DC design decisions that comprehensively account the total costs of ownership (TCO) of DCs inclusive of capital and operational costs..

Currently, DC design practices optimize for the power usage effective metric. However, some industry insiders have expressed that thinking of PUE in isolation may lead to inadvertently increasing the TCO for DC systems. To fill the isolated view of PUE, this research developed a prototype of an agile model that uses life cycle analysis (LCA) frameworks to quantify the holistic life cycle cost of DC systems. The developed model is composed of four software modules:

- A real world internet traffic profile simulation module as a proxy for DC workloads.
- A module that integrates building energy simulations with dynamic DC workloads in a novel way.
- A module that couples the building energy demands with the marginal costs of energy production.
- A module that is composed of a hybrid of a process and economic input-output based LCA frameworks to assess the embodied costs of the global DC system.

As a framework for comprehensive TCOs, this dissertation provides DC designers two contributions. The first contribution is the affirmation that characterising DC costs re-

quires a modular approach. This modular approach is at least three tiered, where the first tier must characterise the infrastructure in terms of materials and operational processes. In the second tier, the model must be aware of the workload interactions within the system. The third and final tier allows the application of objective models to quantify various forms of costs associated with DCs. Using this three tiered approach a demonstration for the total carbon footprint of a set of hypothetical internet service is demonstrated.

The second contribution is shown through the coupling of the network driven workloads and the building energy simulations. The research proves the feasibility of inverse cooling plant controls; where the chiller operational point can be kept at a constant load by varying the IT power loads for batch tasks. Opportunistic varying of batch tasks allows over-subscription of workloads when the cooling plant is at conventional part loads.

This work is dedicated to

... my daughter, to whom it shows that anything is possible given the dedication.

... my parents, who left paradise to give me an opportunity that my ancestors never had.

... my wife, who has shared my sacrifices and paid the opportunity costs along my path.

0.2 Acknowledgements

Architectural design is an artistic and creative craft as much as it requires the ability to resolve programmatic objectives – for not only functional utility of a built environment but also for the life safety of any occupant. In this dissertation I have leveraged the system level strategy from the architectural design framework to propose a novel modeling method that optimizes environmental costs in the data center design process considering variable workloads and renewable energy supply. Through the lens of architectural integration principals this dissertation is a culmination of my cross-disciplinary experience with data centers in the wild. In this research effort I have extracted the pedagogical insights from professional work at Facebook, Baidu, and Google. For each of them I have done data center designs, analysis, deployment engineering, and capacity planning. With my research methodology, believe I diverged from the traditional student to professional path, where in the traditional path students with broad skills transition to a professional role with increasingly narrow purview. None the less, I don't think this research would be complete without my broad area of professional practice, nor would it be complete without the boundless vision of a self-funded academic endeavor.

This fundamental motivation for this research was to find a means to lower the total costs of ownership of a data center with the highest return on investment. It has taken five years to state the problem so succinctly. The formulations of the problem have come from the professional challenges I faced during my design engineering work at Facebook or my research and development work on the full data-center stack for total cost of ownership optimization at Baidu. The problem statement has also been inspired greatly by my experience on the operational decision support front at Google. At Google I have done the last mile engineering on hardware deployments into data centers

and am doing long term capacity planning for some of their software product's now. At the same time, I have deepened my architectural skills and have become conscious to system level trade-offs, no different than triple-bottom-line frameworks in the School of Architecture.

This work is based on my unique understanding of large-scale data centers, a building class that most people may not be familiar with. To concretely provide context, we've all experienced a seeming subtle yet profound technological transformation in most aspects our lives over the last three decades. In one particular aspect it has led to the dematerialization of many things, think Kindle/book, CD/Streaming, and Google Maps/printed maps. While these examples of dematerialization capture consumer facing impacts of technology, I have had the opportunity to witness scale out of their data center infrastructure. It's in data centers that the physical embodiments of tangible products from the past are now materialized. These embodiments are the most significant sink for the environmental costs of these new alternatives.

Unlike other building classes data centers are especially difficult to regulate by traditional building code enforcement and functional performance evaluation practices. An evaluation of its efficacy is a multi-variable optimization problem that involves a complex set of objectives and required deep insight about a cyber-physical system. Optimization of such a complex system requires a systems level architecture spanning across building systems and information technology domains. Driven by business needs the largest internet services have invested in 1,000's of design, construction, and operations staff internally to ensure optimal design, build, and operations. This dissertation is from the viewpoint of one of those design staff. Readers will also find the viewpoint of an ecologically concerned engineer seeking to make globally optimized design decisions through cradle to the grave life cycle analysis of data center systems.

The culmination of this work has been made possible by the continuous support and feedback from the four members of my advising committee. Leading the committee was Dr. Erica Cochran-Hameen, who throughout the research extracted clarity from my cloudy thoughts to help communicate its progress. I am also great full to have had Dr. Gwen Dipietro on my committee as the second member, she provided the thread needed to expand the vision of the research to encompass a comprehensive end-to-end perspective. As the third member Dr. Arman Shehabi's work inspired the undertaking of the research topic initially. Through the research Dr. Shehabi persistently provided the instrumental macro-level awareness of data center impacts from the federal regulation's perspective. The fourth member of my advisory committee, Dr. Ines Azevedo whose expertise on energy grids and work on the higher degree impacts of information technology helped me reason about the complexities of the energy grid and markets. I am thankful to have had the mentor-ship and support from my committee and believe that the direction of the work would have been vastly different without their feedback and references.

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0.3 Introduction

Data centers play a critical role in shaping modern economies and the lives of people around the world. They house information technology (IT) hardware and store data for financial institutions, social media accounts, entertainment portals, and virtual meeting forums amongst many other things. In their physical embodiment, networks of data centers are global scale systems. Within these systems, each data center's size can be as large as a college campus, and consume 100 times the amount of electrical energy every hour as residential facilities do in a day. Moreover, compared to residential facilities, data centers are subject to bulks of accelerated turnovers in technology. This technology turnover results in the housed IT equipment having a useful life that only spans two to three years. Given their breadth, relative power density, and pivoting use-cases, it is extremely important to develop a comprehensive global level modeling framework to help make data center design decisions that have longevity. Today there are several metrics, models, and methods available that allow us to assess energy use of data center systems. At the building scale, the most prevalent metric is the data center power usage effectiveness (PUE). PUE couples the IT loads with the building and it indicates the relative efficiency of the building utilities compared to IT workloads. PUE focused designs have indeed had a profound positive impact on data centers' operational energy use. However, some industry insiders have expressed that thinking of PUE in isolation may lead to inadvertently increasing the total cost of ownership for data center systems. Furthermore, researchers have also pointed out the shortfall of PUE even as an operational sustainability indicator; as it does not consider the carbon performance of the energy source. To fill the isolated view of PUE's through this research I present an agile model that extends the pioneering works of Whitehead [5], Shah [1], and Masanet [6] from a life cycle perspective. My model provides a holistic life cycle cost of data center systems. The model is composed of four software modules. The first module simulates real world internet traffic profiles for 145K Wikipedia pages. The second module simulates the building energy demands using proven data center building energy and scripting interfaces in a novel way. The third module couples the building energy demands with the marginal costs of energy production for a data center's respective region. The final module is composed of a hybrid process and economic input-output based life cycle assessment frameworks to assess the embodied costs of the global data center system. There are two contributions from this work. First, the results of the model affirm that characterising data center costs requires a modular approach. This modular approach must be three tiered, where the first tier must characterise the infrastructure in terms of materials and operational processes. In the second tier, the model must be aware of the workload interactions within the system. Then the final tier can allow objective models such as the EIO, marginal costs of energy, and modeling of other forms of costs. The second contribution is shown through the coupling of the network driven workloads and the building energy simulation. I prove the feasibility of inverse cooling plant controls; where the chiller operational point can be kept at a constant load by varying the IT power loads for batch tasks. Opportunistic varying of batch tasks allows over-subscription of workloads when the cooling plant is at theoretical part loads. A similar form of over-subscription has been implemented by IBM and others with consideration of power management.

Chapter 1

Background and Overview of End to End Modeling Methods

1.1 Chapter Abstract

This chapter presents the methods used to identify the scope of this dissertation's research. These are the methods used to understand and address research questions to quantify the total cost of hyper-scale internet data center building infrastructure. This chapter first reviews the state of the data center industry and makes a case for making them operationally sustainable for business and the environment. Then, similar works that inspire the research hypothesis are reviewed in detail. The review is followed by statements of the research hypothesis and an overview of the dissertation structure. The chapter then provides a detailed overview of the authors understanding of the physical infrastructure that allows for a simple, yet comprehensive end to end model of globally distributed data centers. In subsequent chapters the presented framework is proven to be capable of quantifying the end to end costs of a global system using life cycle analysis methods by demonstrating its effectiveness with the quantification of CO_2 emissions.

1.2 Introduction

This research considers energy and CO_2 inventories across the life time of hyper-scale data centers (DC). These DCs house scalable computational architectures consisting of buildings, cooling plants, power distribution systems, compute hardware, digital storage hardware, and network hardware which are the status-quo for internet service operations. Physically, the size of individual internet DC facilities have increased from modest footprints to now span millions of square feet over the last decade; coinciding with ubiquitous penetration of the internet into the lives of people around the world . The increase in demand for DCs motivates this work as a tool kit in the DC building infrastructure design process. Beyond, the building design process, this kit is intended to be an element for broader business models for internet products.

For internet products, DCs represent a major fraction of their total costs of operations and environmental footprints. This work develops a modeling framework that couples building energy models, marginal cost of grid energy models, and the embodied costs of materials to provide an end to end assessment of data centers. Specifically, this dissertation demonstrates the models by quantifying the CO_2 emissions as a singular metric that is analogous to monetary costs.

Next in Section 1.3, contextual background about the sustainability of data centers is presented. The background indicates the research motivation behind the life cycle perspective for data center systems. Then in Section 1.4, similar works that have analyzed data center life cycle costs are reviewed. These works guide the development of the resulting models from this research by pointing to low hanging fruits and gaps in the current practices. To address the low hanging fruits and fill the gaps, the research hypothesis is stated in Section 1.5 with the overall structure of the dissertation presented in Section 1.6. In Section 1.7, the limitations of the primary data sources are described. The chapter then provides an overview of this research's understanding of data centers in Section 1.8. This understanding of DCs allows coupling of network models with coarse grained representations of the information technology (IT) and building systems. Section 1.9 culminates the various IT and building components from Section 1.8 into deployable units. Section 1.10 concludes the the chapter by summarizing it.

1.3 Background

Data centers (DCs) will consume 13% of the world's energy production by 2030 according to worst case prediction models [7]. This high energy demand is not surprising given the ubiquitous penetration of the internet nowadays. However by factoring technology innovations, some models show a brighter picture. This picture is aligned with current trends, where efficiency across the entire DC stack indicates a downward trend for power demand per unit of performance. As an example, by 2016 the throughput of workloads had increased 350% since 2012 with the same power demand [8]. The hardware efficiency gains seen over the last decade still do not offset the need for additional DC physical capacity.

Internet DC capacity is not bound by physical sizes or geographic locations however. Location agnostic networks spanning the globe allow IT systems to scale in resource parameters such as CPU, GPU, memory, storage, and data access rates. Parametric scaling of these resources enables operational tuning to compensate for physical capacity constraints. Capacity fungibility of DC parameters at a global scale leads businesses with risky practices to provision building scale data-center infrastructure very lean, while businesses that are adverse to risk can be excessively conservative. In the case of lean provisioning, all physical resources are highly utilized with little or no headroom. For the conservative approaches, normal operating conditions are such that sustained operational points are well below the capacity of the equipment. Operations significantly below capacity allows the service to accept bursts in usage, inorganic growth, and be fault tolerant in case of failures elsewhere in the system.

Lean and conservative operations are both classified as equivalent based on today's sustainability indicators and both have strategic advantages for data center owners. For example as a case for conservative deployment consider the abrupt change in internet traffic for many communications, media, and collaboration web sites due to COVID. The excursion in traffic has critical dependencies on data center facility infrastructure. Traffic pattern changes for a set of services are shown in Figure 6.8. In this case if the data centers were operationally loaded to peak capacity then it would be impossible to absorb such drastic changes. However, conservative provisioning has a profound business trade-off in that it may leave resources stranded for a majority of their lives.

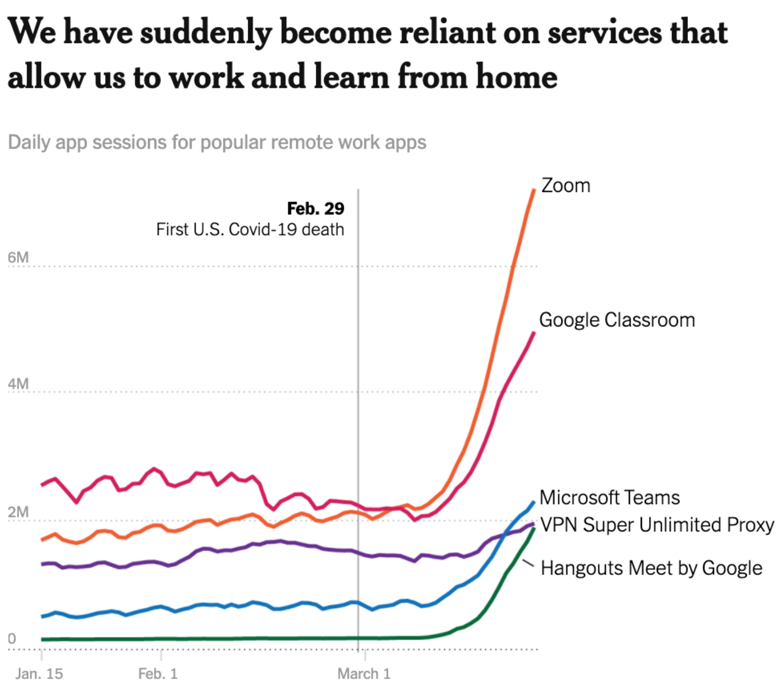


Figure 1.1: Internet Traffic Change. Image from [9]

In terms of capacity, DC facilities can be measured with multiple attributes; power limits, cooling limits, network limits, and floor space. Out of these, power has shown to be the most prevalent indicator of DC capacity, [2]. However, the other attributes don't linearly scale with power. For example, the researcher designed a data center in mid 2013 - sizing the facility on historical trends. By the time the data center was deployed the power density per information technology devices had significantly increased. With the increase in the power density, more than 60% of the designed floor space was left stranded (ie not deployable) as the facilities power and cooling capacity limits were reached at 40% of the designed floor area. However, if the DC design team had looked closer at Moore's law such disruptive change in density were apparent. Figure 1.2 indicates the log-scale nature of de-materialization of transistor based technology made famous by Moore.

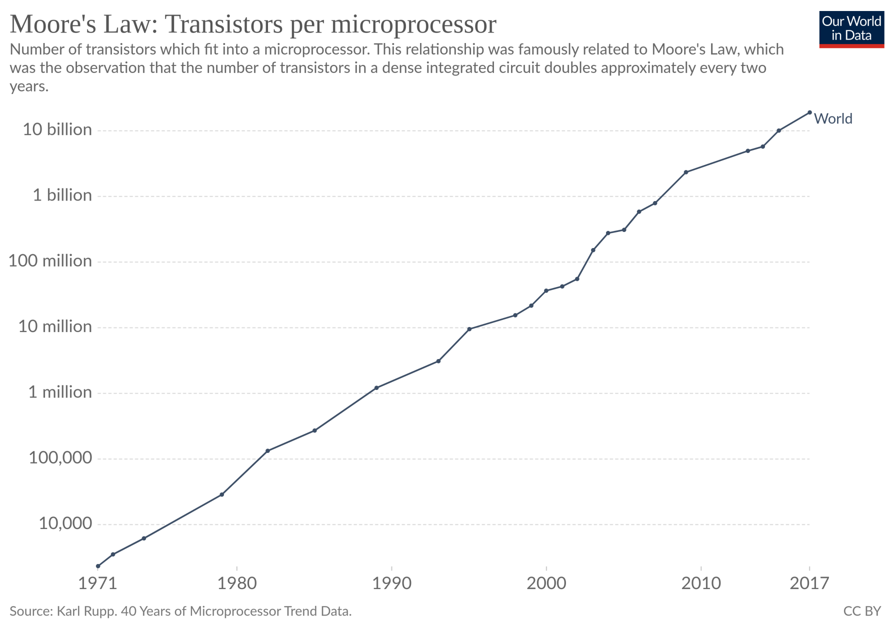


Figure 1.2: Moore's Law: Transistors per microprocessor. Image from [10]

Operationally, the prevalent indicator for sustainability of DC facilities is the Power Usage Effectiveness metric (PUE, see equation 4.1). PUE is a dimensionless ratio of load vs. supply energy. In Equation 4.1, E_{IT} indicates the IT energy load and E_{total} indicates the total energy supplied to the facility. The PUE is generally reported on a quarterly or annual basis by integrating the equation across the respective time period. For a given period, the metric measures the operational efficiency of the facility's system compared to the information technology equipment (ITE). Spaces housing ITE have seen profound cooling and power distribution efficiency gains resulting from the focus on PUE, however the metric does not comprehensively cover sustainability of DCs.

$$PUE = \frac{E_{total}}{E_{IT}} \tag{1.1}$$

E_{total} = Total Power Used at Facility

E_{IT} = Power Consumed by IT Equipment

The PUE's shortcomings as a sustainability metric are noted by Horner, particularly that low PUEs do not correlate to low carbon footprint [11]. The tendency of carbon intensity to vary based on energy source characteristics is demonstrated by Masanet in [12]. Masanet shows that energy supply sources must be coupled with lowered demands to be good indicators of use-phase carbon footprint. For example, the carbon footprint of a low PUE DC with it's energy sourced from a coal plant will be higher compared to a DC that operates with a slightly higher PUE but sources power from a renewable source such as wind. This is summarized in Figure 1.3.

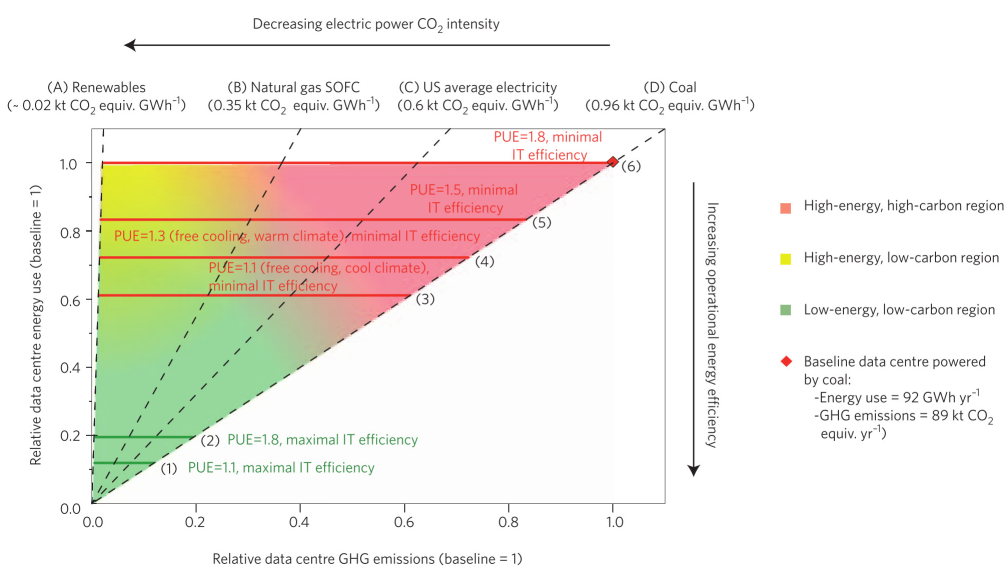


Figure 1.3: Energy Use vs. Carbon performance map. Image from [12]

From positive point of view, using PUE as the de-facto energy efficiency metric led ASHRAE to recognize the significance of the cooling systems to the data center energy use. In rapid response they developed guidelines to help operators optimize their cooling systems. One of the most profound contribution from ASHRAE has been their position on expanded thermal boundaries for the data center environments, as indicated by the black boundaries in the pyschrometric chart shown in Figure 1.4. The expansion is relative to a static cooling set-point temperature of $55°$F that was standard practice for legacy operations. The expanded thermal boundaries have an influence on nearly all elements of a data center facility during their design phase, but most importantly ASHRAE's guidelines for the expanded thermal boundaries has helped facilities operators configure their cooling plants to minimize the energy use and lower their PUE.

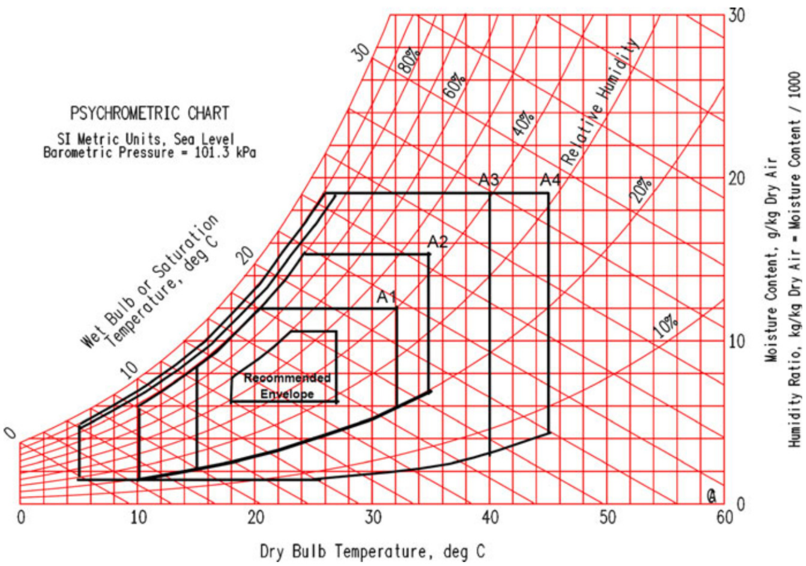


Figure 1.4: ASHRAE thermal boundaries for data centers. Inlet air temperature of IT equipment (©2011 ASHRAE). Image from [13]

A facility's thermal environment directly couples the IT and building systems. The first order impacts of this coupling are on the cooling system; spanning from the cooling tower to the node junctions for the nano-scale transistors. The end to end flow of the heat rejection is shown in Figure 1.5.

However, there are also many second order effects that must be taken into account when developing disruptive designs that deviate from the heat rejection paths shown in Figure 1.5. When deviating from these legacy practices, trade-offs across the entire life

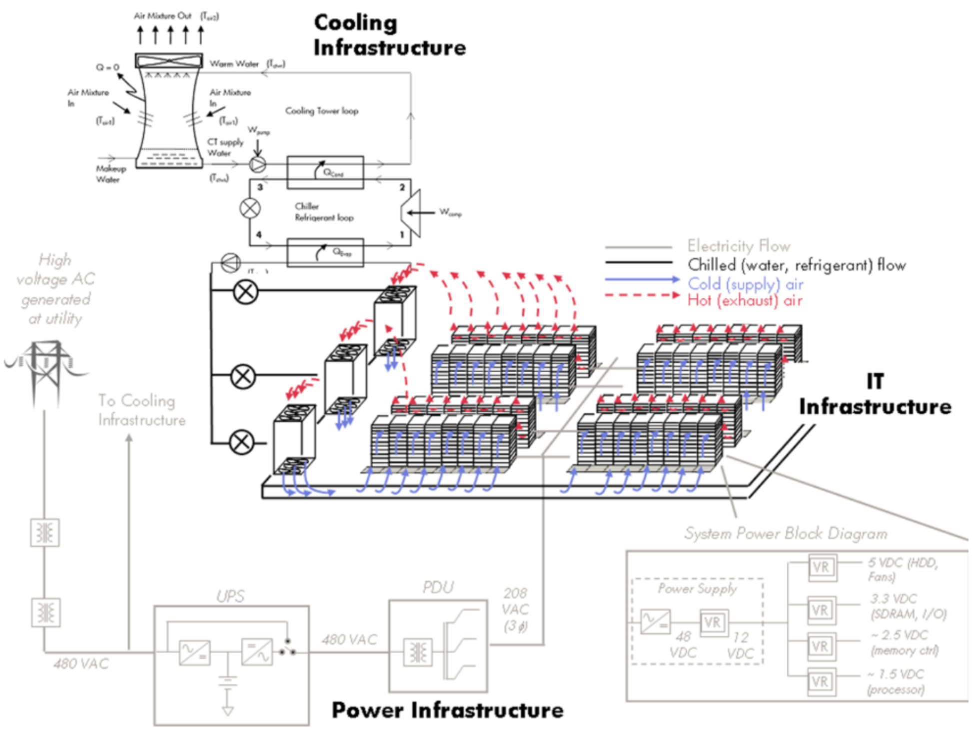
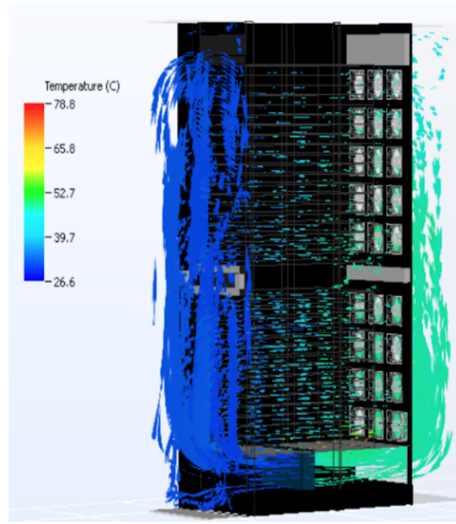


Figure 1.5: DC Infrastructure Heat Rejection Paths. Image from [1]

cycle of the system must be characterised. As an example, the researcher's need for a life cycle analysis framework was recognized during the development of a novel bottom-cooled hermetic rack [14]. The test chamber for the cooling coil and the computational fluid dynamic model of the bottom-cooled rack is shown in 1.6a and 1.6b, respectively. This development alone required a deep trade-off analysis of various systems that could be most appropriately be done with a life cycle analysis framework.

Specifically for the bottom cooling unit; the second order trade-offs included the changes to the building systems, it's impact to the network topology, chiller plant augments to support revised thermal requirements, and power distribution changes due to changes in the rack power densities. These trade-offs required awareness of the data center service level agreements as not to strand space, power, or network ports. Furthermore, the business evaluation of such a development effort had to consider all of the above factors to indicate cost vs. performance for comparison with alternate technologies as shown in

(a) BCU Air Flow Chamber



(b) BCU Rack

Figure 1.6: Development of Bottom Cooling Units. Image from [14]

Figure 1.7.

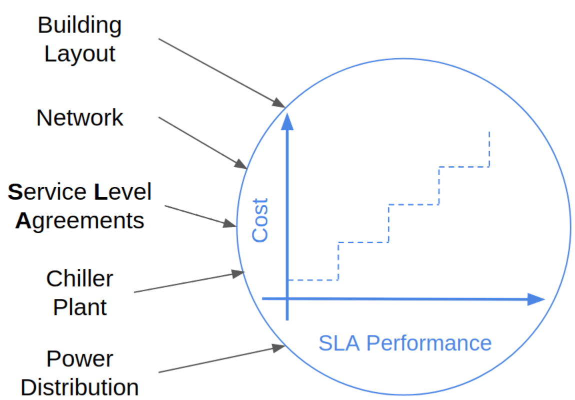
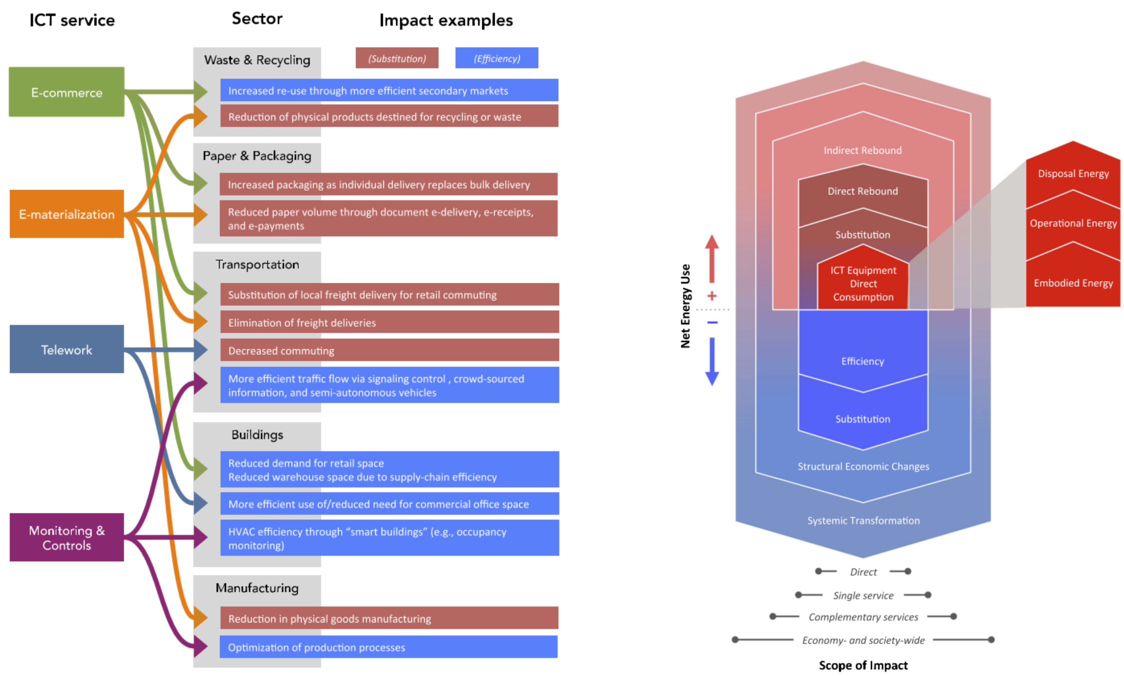


Figure 1.7: Second Order Trade-offs.

Beyond the operations phase of DCs, the IT hardware and physical infrastructure products they're composed of have many other life-cycle phases. At each life cycle phase of the products, there are energy and CO_2 inventories. With life cycle analysis (LCA) principles these inventories can be tallied from their raw form to their useful state. The LCA perspective allows the treatment of these inventories as either a debt or credit to it's environmental footprint. The debt and credit approach follows a structure analogous to



(a) Influence and Impacts of ICT to other sectors (b) Taxonomy of ICT impacts

Figure 1.8: Higher Order ICT Impacts. Images from [17]

total costs of ownership (TCO) methods used in today's sophisticated business models for DCs [15]. These modern business models amortize capital and operating costs over a system's useful life similar to LCA. This research therefore threats CO_2 as analogous to monetary cost and demonstrates the end to end CO_2 inventories in this dissertation.

The direct effects described so far and discussed throughout this work are the most transparent impacts associated with information communication technology (ICT). The indirect or higher order impacts fundamentally alter the use of energy in a wide breadth of applications. Figure 1.8a shows examples of the breadth ICT impacts to other industrial sectors. However, this research followed the approach set by The Green Grid where the DC is a physical entity of interest and focuses on the assessment of it's direct life cycle activities [16]. The direct activities are indicated by the red enlarged area shown in figure 1.8b which sets the boundary conditions described later.

1.4 Similar Works

Now, pioneering works that have quantified the life cycle costs of DCs are presented.

The most explicit DC life cycle cost assessment is reported by Whitehead [5]. Whitehead proposes guidelines and criterion for DC life cycle assessments in-line with International Standards Organization (ISO) 14040 [18]. Whitehead's report is reflects the LCA of a UK DC with legacy infrastructure. Using the LCA results of the UK DC as the benchmark, they evaluate a Swedish DC with state of the art infrastructure and a much higher server stock turnover (refresh) cycle. The boundary conditions and life cycle phases of both LCAs are shown in figure 1.9. Whitehead finds that refresh cycles have the most significant contribution to the life cycle impacts in today's state of the art DCs compared to legacy DCs where the operational energy dominate. In this dissertation, Whiteheads functional-unit of *1 kW of IT per year in a Tier III facility* is adapted as a reasonable unit of measure of data center functionality.

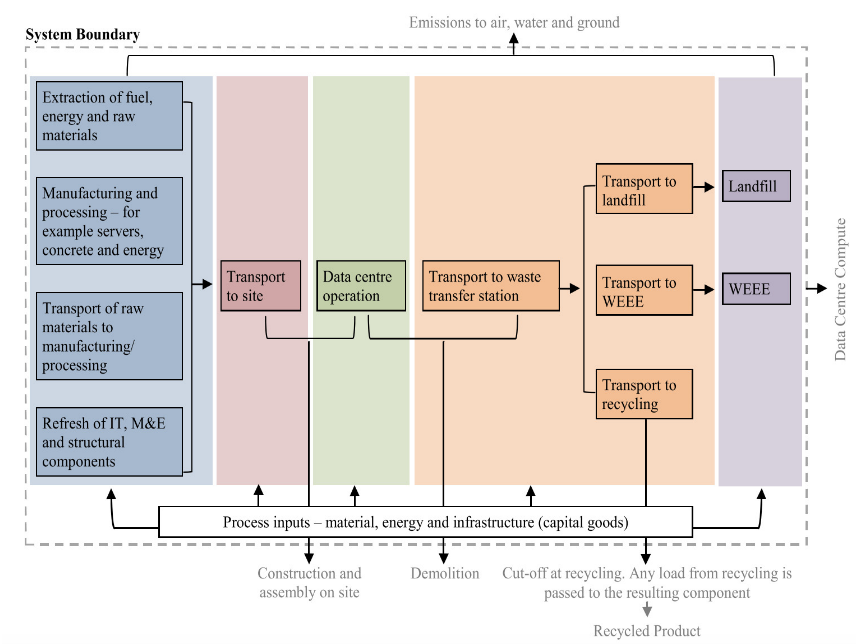


Figure 1.9: System boundary for DCs. Image from [5]

The Hewlett Packard Corporation published a series of papers around the sustainability of information technology sector in the early 2010's. Two of the most relevant to data centers were led by Shah and Chang [1, 19]. In the first work, Shah demonstrated the use of the economic input-output (EIO) model for assessing the embodied costs of the major infrastructure categories found in data centers (see Table 1.1). Their development of the environmental model for the data center was ultimately a combination of process based and EIO methods. Building on Shahs's EIO based framework, Chang uses the thermodynamic metric of exergy to quantify data center sustainability. By quantifying the irreversible thermodynamic processes in terms of exergy allows normalization in terms of architectural parameters [19]. A parametric view enables systems designers to reason about only an intuitive set of constraints.

Infrastructure Category	Infrastructure Parts
Compute infrastructure	Compute servers
	Storage systems
	Network equipment
Cooling infrastructure	Computer Room ACs
	Chillers
	Cooling Towers
	Pumps and Piping
Power Distribution	UPS
	PDU
	Cables
Built infrastructure	DC shell

Table 1.1: Components considered by Shah [1]

In addition to the independent LCA perspective of Whitehead and the corporate perspective of Hewlett Packard, the Department of Energy's Lawrence Berkeley National Lab has produced the CLEER online modeling tool [6]. CLEER is a web based user interface that allows consumers to model the migration of on-premise software workloads to cloud based data center platforms. As shown in Figure 1.10, the charter for the CLEER model is to consider the end to end energy associated with cloud services.

In the subsequent chapters, this research builds upon these pioneering similar works described above. Six parameters common to all three are identified and supplemented with novel contributions developed by this dissertation research. Two additional parameters are also added by this dissertation's end to end modeling framework. Namely, the framework presented in this work are also inclusive of network traffic and building opera-

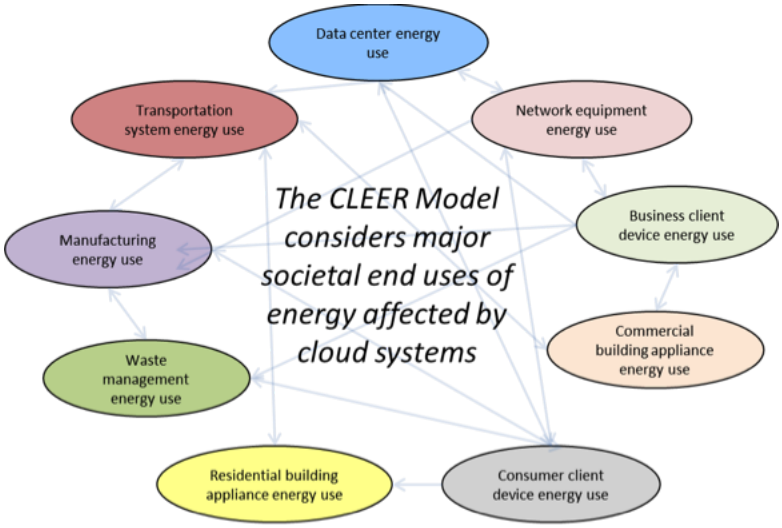


Figure 1.10: CLEER Framework. Image from [6]

tions as shown in Figure 1.11.

	Operation	Embodied	IT	Network Aware	Building	Dynamic	Energy	Carbon Footprint
Whitehead	🌍	🌍🌍🌍	🌍🌍		🌍🌍		🌍🌍	🌍🌍🌍
Shah	🌍	🌍🌍	🌍🌍		🌍		🌍	🌍🌍
CLEER	🌍🌍	🌍🌍🌍	🌍🌍🌍		🌍		🌍🌍	🌍🌍🌍
Kumar	🌍🌍🌍	🌍🌍🌍	🌍🌍🌍	🌍🌍🌍	🌍🌍🌍	🌍🌍🌍	🌍🌍🌍	🌍🌍🌍

Figure 1.11: Gap Matrix.

The background discussed in this section inspire the research question of this dissertation. Namely the research question is *how can DC designers make decisions that have longevity with all of the uncertainty involved?* Next in Section 1.5, the research hypothesis is stated followed by an overview of the dissertation's structure that validate the hypothesis in Section 1.6.

1.5 Hypothesis

To make effective DC design capacity decisions, the decisions must be based on scalable and agile models.

Sub hypothesis are as follows:

1. The model needs to assess end to end cost trade-offs and be technology agnostic.

2. Monetary cost models for DCs are analogous to environmental cost models. LCA modeling community has proven its effectiveness for analysing global scale systems and supply chains.

1.6 Structure of Dissertation

This research is composed of four modules that culminate academic experiments and analysis with extensive professional experience in designing, planning, building, and deploying data center systems through out the world. The modules are presented in this dissertation as independent, but correlated chapters. The segmentation of the chapters roughly aligns with the software modules developed as shown in Figure 5.5.

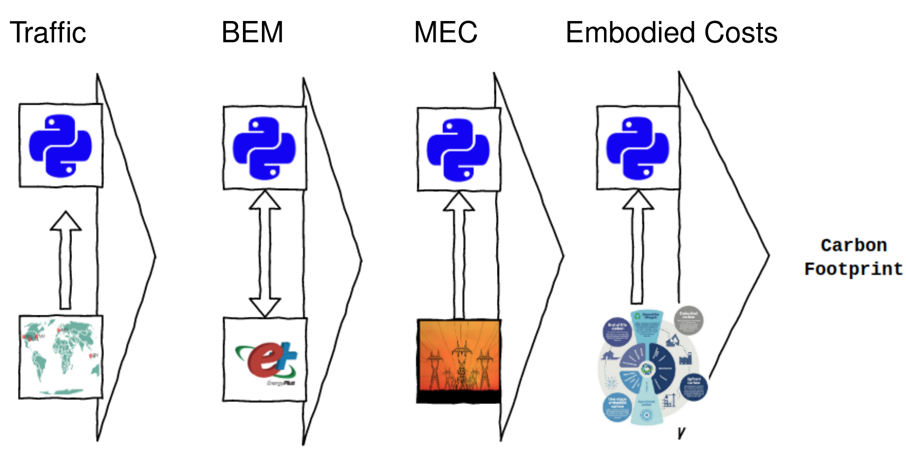


Figure 1.12: Model Process Flow Diagram.

1.7 Note on Data Sources

The underlying data sources that construct and validate the developed software modules are sourced from publicly available references and professional heuristics. Generally, the preference of this research is to use publicly available data for academic posterity, however there are several critical pieces of information that can not be publicly disclosed. In these cases, where no relevant public information was found, the author leans on professional heuristics.

Due to the nature of the technology business, most of the heuristically derived data points are protected under non-disclosure agreements. Every effort is made not to impede these agreements.

1.8 Overview of Data Center Systems.

The research's understanding of data centers and the various systems with-in them are now presented. The first set of systems addressed are the IT equipment. The IT equipment are viewed as an ensemble at a building or cluster level (see Figure 1.15). Viewing data centers as an ensemble of IT equipment allows for a simpler model while aligning with the single coherent views that are objectives of services that are supported in these clusters. From a service perspective, the physical implementation is agnostic of whether the functional components are aggregated within a chassis or the components are dis-aggregated across chassis provisioned with homogeneous components. In the later case, high speed local area networks are critical for orchestration of service execution.

The second set of systems addressed are the data center communication networks. As described above networks are a critical component at the core of hyper-scale data centers. It's the network that allows data center services to appear to its users as a single coherent system whether the physical components are located in the same building or they are globally dispersed [20].

The third system addressed in this section are the building systems. The building systems are the key focus of this research and this section aims to identify the key parameters that make data center facilities distinguishable from other building types. Using the combination of distinguishable parameters and a baseline building sector from the USEEIO [21], the baseline costs input vector (Y-vector) is presented.

The following subsections provide overviews of the IT equipment, communications networks, and buildings as they are reasoned about in this research.

Information Technology Equipment (IT)

The modeling framework developed in this research is founded upon the IT equipment housed inside data centers. Table 1.2 indicates the data used in this research to characterize the IT equipment, which are inputs to building energy simulations and embodied materials models. The computation and storage IT equipment (servers) profiles are based on production server configurations of a large internet operator (under NDA), representing their deployments in 2015 and 2016. However, the objective of the research is to have the agility to model allocation of any component found in data centers. In that light, some of the current approaches for allocating servers and their components are described next.

Servers are generally categorized as compute nodes or storage nodes. Compute servers may be fitted with state-of-the-art processors, input and output devices, and dynamic random access memory (DRAM). The latter category of storage servers are optimized for high density storage with minimal processor capabilities with input output devices selected based on the desired performance. Figure 1.13 shows air cooled server units fitted with a combination of processors and DRAM, while Figure 1.14 shows a homogeneous arrangement of storage drives in a server.

Segregating the storage from the compute instances have several advantage for the

Figure 1.13: Compute Servers - (Top) Intel Haswell-based server tray and (Bottom) IBM Pow-er8-based server tray. Images from [22]

Figure 1.14: Storage Servers - Homogeneous Storage Server Tray. Image from [23]

software architecture; for building systems designers the most intuitive is failure isolation and operational diversity. For consideration of failure isolation, the outage of a single compute instance will also result in the stored data becoming unavailable. In terms of diversity, when compute devices and storage devices are on the same physical chassis, a single compute processing device may not be capable of handling all the requests to access the stored data within performance bounds. Separating the data into different servers allows the incoming read or write requests for the stored data to be balanced across a set of processors based on performance bounds. This relationship is the premise of many modern data center cluster designs, where stored data and compute resources are strategically arranged. Figure 1.15 indicates such a cluster storage hierarchical scheme from Barroso [2].

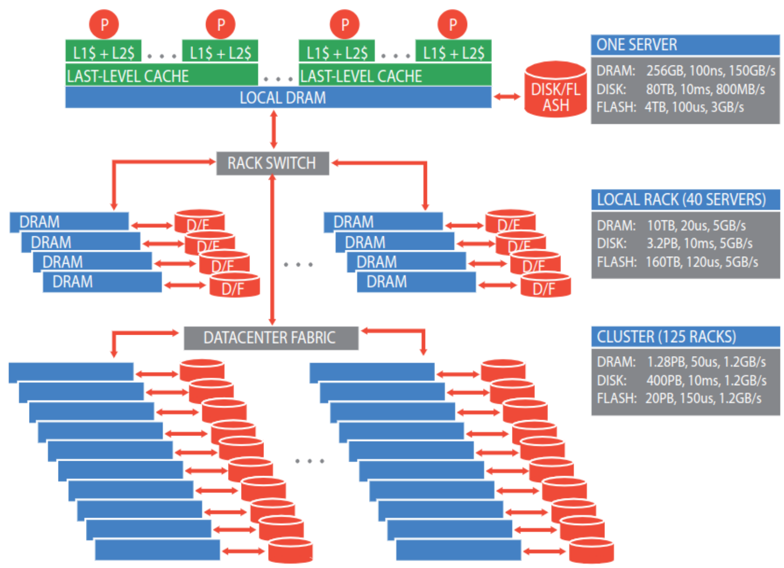


Figure 1.15: Storage hierarchy of a warehouse scale computer. The concept of a cluster loosely follows this topology. Image from [2]

In this work, servers with a combination of compute and storage components are characterized for power as listed in Table 1.2. The power demands of these components are obtained using the individual power requirement for each component from Table 5.4. The combination of component counts and individual power values together quantify the total power of the servers. In the servers studied, their total power demand range from 320 watts to 334 watts (see Total Power row in Table 1.2). These heterogeneous server

Comp Count / Server Power	Comp. Power	Count_{SSD}	Total Power_{SSD}	Count_{HDD}	Total Power_{HDD}	Count_{IO}	Total Power_{IO}	$\text{Count}_{Compute}$	$\text{Total Power}_{Compute}$	Count_{LM}	Total Power_{LM}
Example Function		MaReduce		Photos Sharing Application		General Purpose High IO		Online Retail Search		General Purpose Compute	
CPU	105	2	210	2	210	2	210	2	210	2	210
MEM	0.375	8	3	8	3	6	2.25	4	1.5	4	1.5
HDD	3.87	4	15.48	8	30.96	2	7.74	4	15.48	8	30.96
SSD	0.37	2	0.74	0	0	5	1.85	0	0	0	0
MBD	40	1	40	1	40	1	40	1	40	1	40
PSU	25	2	50	2	50	2	50	2	50	2	50
BAL		1		1		1		1		1	
Total Power (W)			319.22		333.96		311.84		316.98		332.46

Table 1.2: Server types and component counts within them as used for simulations performed for this research. The Count columns indicate the component counts in the server type denoted by the subscript. The server types are correlated with Figure 5.6

choices are used in the models for three reasons:

1. The research had first hand access to representative cost data for these servers under NDA.
2. Mixed component server assemblies can properly characterize the embodied materials of the overall DC by linearly scaling the power or count of the components.
3. Mixed server types allow the components to be quantified by packing the fractional power demand of each component with-in the server into the total power of the DC. The method for packing various component types into the DC is indicated in Algorithm 5 (see IT discussion in Section 5.3.4).

Using the heterogeneous servers captures all of the components that influence the developed life cycle cost models. Finer resolution is not sought as the models that are developed in this research don't account for the airflow patterns or the IT rack layout inside the buildings. Nonetheless, the fidelity of the framework can be enhanced for quantifying the operational energy if the physical layouts of the servers are more precisely characterised.

The servers discussed above are housed in steel racks as shown in Figure 1.6b and Figure 1.16. At the rack level, collocated servers can communicate over switched network links within the rack (see Figure 1.17). Racks can also communicate with other racks, bridged by high speed communications networks across local areas (shown as network Ingress/Egress in Figure 1.17)) . Communicating racks are constrained by the software application's latency bounds. The communication latency values (a measure of communication delay) are attributes of the optical instruments and cabling system as discussed in the Network part of Section 1.8.

The choice for the hardware arrangement is reasoned about as performance objectives for specific workloads that the rack will be susceptible to. In the end whether at the individual server, rack level, or cluster level, compute and storage devices need to communicate with each other as shown in Figure 1.15. Specific design choices must optimize the service level performance objective in terms of processing speed, data volume, read-/write latency, and the read/write rates. Performance optimization can by characterized by analysing the system through queuing theory. Applications of queuing theory relative to computer systems is presented by Harchol-Balter in [24].

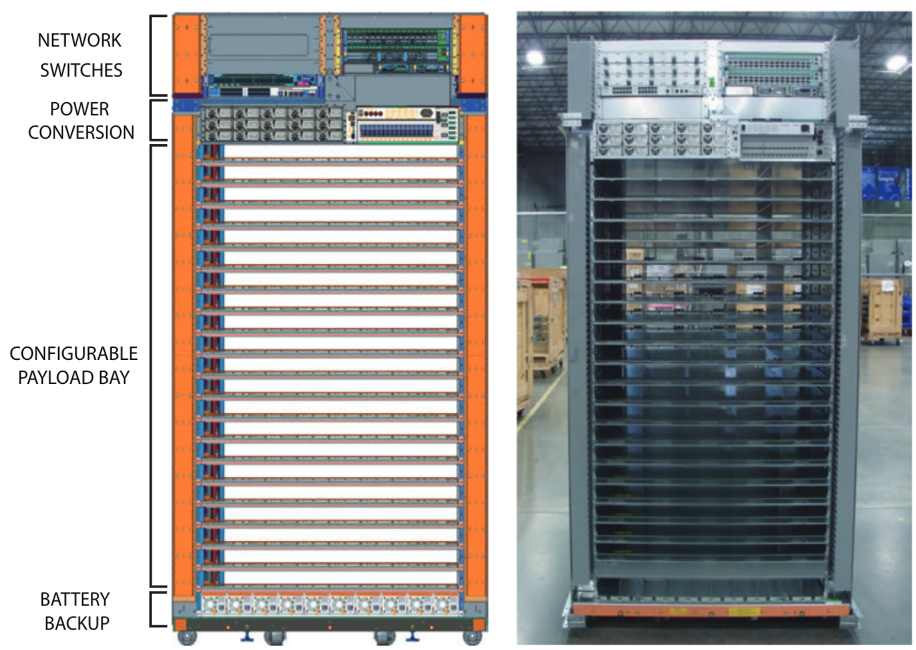


Figure 1.16: Server rack with top of rack switch, power shelf, server trays slots, and local batteries. Image from [2]

The server rack shown in Figure 1.16 illustrates the arrangement of local power conversion, power storage (batteries), and network devices along with the server payloads. This rack is indicative of a typical rack found inside Google's data centers as discussed by Barroso [22]. At the rack level, the incoming power feed is generally alternating-current (AC) voltage while all the server components require direct-current (DC) voltage. In legacy servers the AC to DC voltage conversion happened within the server, however in modern racks the power is rectified at the rack level with more efficient rectifiers that feed DC voltage to bus-bars for distribution to servers [25]. The rectification external to the servers leads to some additional heat at the rack level in addition to the heat dissipated by the server components. In many rack configurations, all servers are connected to top of rack (TOR) switches. These TORs are the hub for all the server's communications cables. The network connections are discussed further in next subsection.

Network Model

This subsection provides an overview of data center networks. This understanding of the network allows the research to abstract the building level power demands based on simple server form-factors as discussed above and motivates the network correlated building energy models presented in the subsequent chapters, where the building energy power and cooling loads are reset based on ingress network traffic to a data center building. For internet scale computing, the large data sets required simply do not fit on any single machine. At the building/cluster level, processes running on CPUs require instructional and process data that maybe stored in remote racks. Therefore local area network (LAN) fabrics between servers is critical for allowing CPUs to access remote storage devices [26]. Furthermore, services operating in geographically remote buildings also require communications with each other over wide area network (WAN) for performance and availability objectives. A generic network topology is shown in Figure 2.1.

To illustrate the communications at the rack level, a schematic server rack arrangement with it's network connections is indicated in Figure 1.17. In this arrangement, servers can communicate with other collocated servers in the rack through the top of rack switch. This is sufficient for relatively small services and is a reason to mix storage and CPU servers at the rack level. However, as discussed above it is not trivial to provision static dependencies between processes and stored data for global scale services, so distributed systems design principles must be exploited [20]. In distributed systems, external connections to and from the rack is essential for not only accessing data or processes that aren't locally available but also for things like replication and communications with the service users.

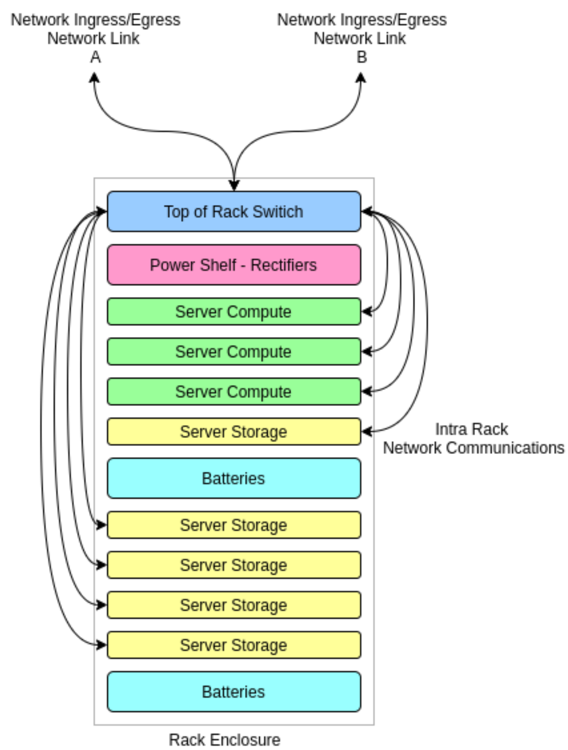


Figure 1.17: Server Rack Communications Network. The quantity of server slots is shown for clarity, a typical rack may host up to 40 server chassis.

As discussed above, when processing and storage servers are not collocated on a rack, they are bridged together with high speed communication networks. A collection of densely connected servers and racks over a communication network is commonly termed a cluster. A popular network topology within clusters is illustrated in Figure 1.18. The physical layout of the cluster is limited by the fiber optics and cable systems. The distance limits for multi-mode fiber cables used inside DCs are indicated in Table 1.3. Beyond these limits communication delays and data transmission quality become impaired.

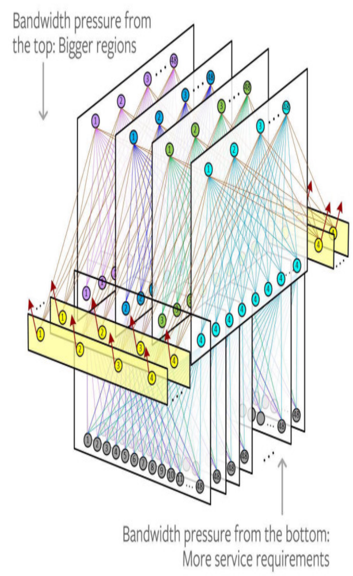


Figure 1.18: Data Center Clos Cluster Network Fabric. The four planes at the top aggregate the communication links from each rack. The nodes shown at the top of the plane indicate aggregation switches and the nodes shown at the bottom indicate each rack's TOR switch. The lower planes represent server racks, with the gray nodes indicating individual servers. In this arrangement each rack's TOR switch has four logical links, with each link densely connected to all switches in the isolated aggregation planes. The yellow planes represent the edge of the cluster network, it provides communication with remote clusters and external systems. Image from [27].

Cable Type	10 Gb Ethernet Distance	40 Gb/100 Gb Ethernet Distance
OM1 Fiber	33 m / 100 ft	N/A
OM2 Fiber	82 m / 260 ft	N/A
OM3 Fiber	300 m / 1000 ft	100 m / 330 ft
OM4 Fiber	400 m / 1300 ft	150 m / 500 ft

Table 1.3: Communication capacity distance limitations. Data sourced from [28].

The next section presents this research's understanding of data center building systems.

Building Systems

In this subsection the DC facilities and the motivating factors for their design attributes are described. The building attributes that guide this research are obtained from real world hyper-scale designs. In subsequent chapters and in the developed models, the building attributes discussed here are coupled with real project cost data. Specific building designs are not explicitly disclosed in this dissertation and the cost data have been normalized across the set of real world examples based on provisioned capacity of the respective data centers.

The form factor of data center facilities are heavily influenced by the mechanical systems conveying heat from the server components to the outdoors. Figure 1.19 illustrates the airflow path across a data center from the point that air enters the building to it's point of exhaust from the building. In addition, its generally the mechanical system that constrains the layout of the servers inside the facilities. The mechanical constraints make it's coordination with all the IT and other utility systems a critical part of the DC design process. Figure 1.20 illustrates racks laid out in arrays of contiguous rows. The air space between the rack rows are segregated for either hot or cold air, where the front of the servers are against the cold aisle and the back of the servers are against the hot air aisles.

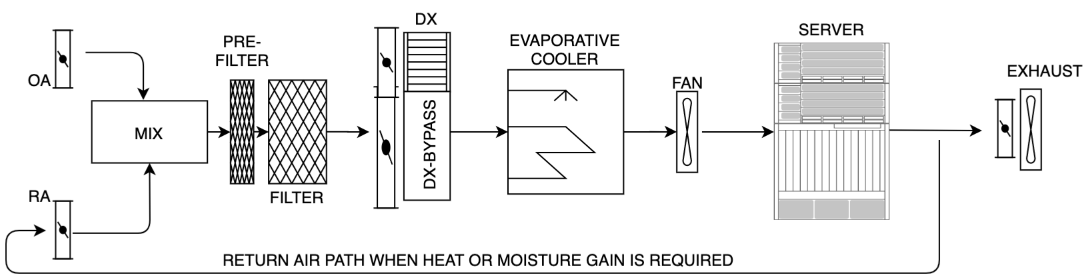


Figure 1.19: Generic air flow path in server rooms for an outside air cooled facility.

Another influential DC attribute is their power density. In the set of designs reviewed, power density ranged from 1.99kW per meter-square to 3.3kW meter-square. This range of power density requirements make data centers distinct from conventional buildings in some respects, while in other respects DCs are similar to conventional buildings. Nonetheless, the dissimilarities between DCs and conventional building prohibit environmental cost modeling of DCs directly into economic input and output (EIO) frameworks as discussed in Chapter 5.

To compensate for the difference between DCs and conventional buildings, Shah has

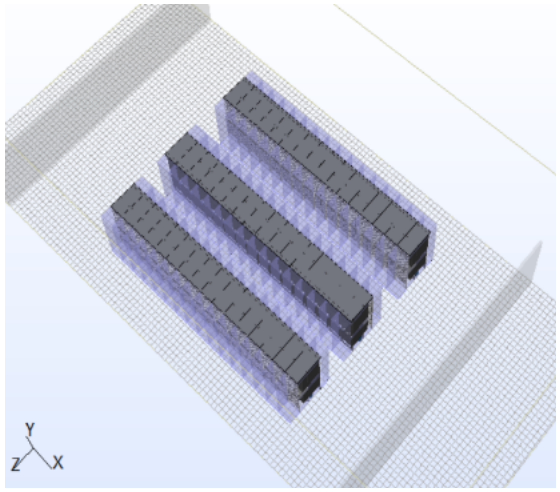


Figure 1.20: Server room layout. The gray elements in the figure are the hot aisles and the light purple elements are the server racks. The objective of the cited work was to determine the optimal spacing of adjacent racks across hot-aisles. Image from [29]

demonstrated an effective method that augments the conventional buildings represented in publicly available EIO models [1]. This research uses Shah's method, but substitutes it's legacy EIO with the 2017 United States Environmentally Extended EIO (USEEIO). The USEEIO reflects newer economic relationship between sectors and is indicative of more recently evaluated environmental costs incurred by the respective sectors per unit of monetary cost [21].

Sector	Relative Costs
HVAC Equipment	0.55
Turbines and turbine generator sets	0.77
Transformers	0.05
Switchgear and switchboards	0.1
Communication and energy wire and cable	0.1
Other miscellaneous electrical equipment and components	0.04
Relay and industrial controls	0.146
Manufacturing buildings	5.244

Table 1.4: Relative costs of DC building systems per watt of power. These costs are scaled up based in the facility's power capacity in the EIO model.

Table 1.4 reflects the costs of the buildings and the incremental costs of specialized systems relative to a Watt of provisioned capacity. The costs are spent during the data center construction for goods supplied by the listed sector. The relative costs representation allows the building costs and specialized systems costs to be scaled based on the total provisioned power. The manufacturing building sector is selected from the USEEIO as being the most similar to data centers and used as the baseline for the input vector into the USEEIO. All the other systems contribute incremental cost increases to the manufacturing building cost. Nonetheless, the values in the table can be adjusted to analyze specific data center designs

In the next section, the above systems are tied back to the explicit interface between building attributes and IT systems.

1.9 Tieing it all back to deployable increments of IT equipment

DCs are often populated on an incremental basis. The deployment increments are typically at the resolution of a rack, as racks provide a clear interface with the building systems. For example, when the racks are independent failure domains they can be easily isolated with a dedicated electrical circuit breaker at this level. Also, a fully populated rack is much easier to reason about for capacity constraints from a power and cooling standpoint then deploying at the extreme resolution of a single chassis at a time.

On the other end of the extreme is the step-wise deployment of servers to consume the entire power capacity of a building or cluster. This extreme may lead to expensive and rapidly depreciating hardware to be under utilized as the service demands ramp up over time. The service ramp rates motivate most DC operators to deploy hardware at rack level increments described above under just in time practices. Albeit, there are exceptions that make step-wise full capacity deployments an attractive option as exemplified by the sudden increase in demand shown in Figure 6.8. However, even in such cases the IT manufacturing supply chain may become the bottle neck, ultimately resulting in rack level incremental deployments.

Capacity constraint management is one of the most critical aspects of data center operations, as IT devices can be added, removed, and replaced at any time during the life of the facility. Deployment of partially populated racks risks capacity being stranded (i.e. headroom on the electrical circuit capacity that can not be used else where in the electrical system) or over-subscription of resources when the end state of the power demand for all the deployable rack positions are not deterministic. To reclaim the stranded power or to alleviate the over-subscription of power may require re-shuffling of racks across a data center to de-fragment the floor space. The cost of rack moves includes the down time of a rack and staffing/engineering toil and is handled with resistance in practice.

In the models developed for this research, for simplicity and its purpose as a proof of concept framework, the end state of the the data centers are evaluated without regard to the increments of deployment where the servers are all packed into the power capacity of the building. The specific server configurations that are considered in this research are indicated in Table 1.2. These components are packed into the power envelope per Algorithm 5 (see Chapter 5) to quantify the input costs for the USEEIO. This level of aggregation may suffice for monolithic clusters. To translate the components into the count of deploy-able racks, requires additional insights about the server rack layouts in relationship to the rest of the building floor area. Algorithm 1 presents the methods to translate the server power density to rack counts and rack level power.

Equation 1.2 indicates the IT load density of each thermal zone. However, this density is a naive distribution of the IT load over the entire floor area; while servers can only be positioned in linear rows as shown in Figure 1.20. This rack layout reduces the area available for racks. To account for the fraction of the server floor where racks can be deployed, the available area for racks can be calculated with Equation 1.3. Once the area for racks is known, the quantity of racks that the server floor can support can be evaluated with Equation 1.4 and the average power for each rack can be evaluated with Equation 1.7.

In Table 1.5, power capacity, building area, server rack dimensions, and the network coefficients are input based on the specifications of a 7,500 kW DC. By using this method, the average supportable rack power is evaluated to be 6.5 kW. As discussed above, the

Algorithm 1 Rack Counts from Building and Power Properties

$$\rho = \frac{P_f}{A_F} \tag{1.2}$$

$$A_r = A_f \times F_f \tag{1.3}$$

$$R_\# = \frac{A_r}{R_a} \tag{1.4}$$

$$P_{rs} = \frac{P_f \times (1 - F_n)}{R_\#} \tag{1.5}$$

$$P_{rn} = P_{rs} \times F_n \tag{1.6}$$

$$P_r = P_{rs} + P_{rn} \tag{1.7}$$

Where:

ρ = Power Density of server floor. This value is used in the EnergyPlus Models.
A_f = Total floor area.
A_r = Area available for rack deployment.
R_a = Rack footprint area.
$R_\#$ = Rack count.
P_f = Provisioned power for IT for server floor.
P_{rs} = Power for rack server equipment.
P_{rn} = Power for rack network equipment.
P_r = Average power of racks in the DC.
F_f = Fraction of A_f that is deployable with Racks.
F_n = Fraction of power to rack allocated to network devices.

power demand of each type of server from Table 1.2 ranges from 320 Watts to 334 Watts, therefore each rack can support 20-21 servers without power over subscription at the rack level.

There are several other constraints that must be optimized in real world data center deployments. The optimization may include power phase balancing, network bandwidth, network ports, heat rejection rates, air flow rates, along with several other fluid mechanics considerations. Each of these must be addressed on a situational basis but they are not

Variable	Value	Units
A_f	3778	m
F_f	0.15	%
P	7500	kW
R_a	800	in^2
R_a	0.52	m^2
P_{rn}	0.05	%
ρ	1.99	kW/m^2
A_r	566.7	m^2
R	1098	each
P_{rs}	6.5	kW/rack

Table 1.5: Example of rack power for server floor power density values.

accounted for in the developed framework.

1.10 Conclusion

This chapter presented the background on the current state of the data center industry and it provided a review of the inspirational work that led to the research hypothesis. The chapter also presented an overview of three technological segments found in data centers; namely IT equipment, building systems, and network. Accurately modeling these three segments is the path to high fidelity data center models. The overview in this chapter demonstrates the author's understanding of data centers and indicates the research's specific use cases and limitations across these technology segments. In the next chapter a wide area network based building energy model is presented.

Chapter 2

WAN Based DC Energy Simulations for Internet Services

2.1 Chapter Abstract

Data centers (DCs) are a critical component of modern day economies and social lives of people all around the world. In many aspects society's dependency on internet services enabled by DCs is still increasing; the COVID-19 stay in place orders are a current example of unprecedented growth rates for many internet services. With the increasing dependency on DCs, there is a concern about their environmental impacts. Reasoning about the environmental footprint of these globally spanning infrastructure systems requires new approaches for modeling energy use of facilities within these systems. This work demonstrates such as model with a prototype of a top down software module that simulates the traffic profile for a globally distributed internet service. Using Wikipedia as the exemplary internet service, the developed simulator's results are used to reset the IT loads in EnergyPlus to quantify the power demand required to operate all the buildings within the network of Wikipedia DCs.

2.2 Introduction

DCs are ubiquitous in today's society. Consumers of DC enabled web services expect high availability of their functionality and access to their data on a continual basis. These expectations are met with software architectures that provide strongly consistent views of the data regardless of location and in the presence of physical systems failures. In terms of specific failure modes, network failures can be the most catastrophic. For example, an outage of a network link connected to a DC can lead to all it's physical resources to become inaccessible from the outside. With these expectations, the dependencies between internet DCs and their communications network during failures is clearly apparent.

The utility systems (such as mechanical cooling and power distribution) and the network connections of a DC are not only coupled in failure scenarios described above, but they are in lock-step with each other during normal operations too. This coupling of network and building systems is easy to reason about as internet DCs don't generate workloads hermetically. The workload demands for DCs come from remote consumers (user facing traffic) and other adjacent DCs (back-end traffic). Both forms of incoming traffic instantiate computational and storage processes on the IT hardware, which in turn are powered and cooled by district scale distribution plants.

In the current generation of DCs, the building utility systems demand less than 10% of the total energy delivered to the site [30]. The balance of the power of these new DCs is consumed by the information technology (IT) equipment. With this disproportionate allocation of energy, it is clear that the total energy use in DCs is more sensitive to IT loads than the facilities systems. Yet the building systems still receive the most attention in the design and facilities operations phases of the buildings. Others have pointed out gaps in the current DC building energy modeling practices as-well [31].

To provide an intuition of DC networks, Figure 2.1 shows a generalized depiction of their topology. At the top, the internet service provider (ISP) networks are shown as clouds because the physical paths of these systems are managed by the global ISPs and are typically out of the control of DC operators. DC operators depend on the ISP's physical infrastructure for connecting their geographically remote facilities with private wide area networks (WAN). The pink links indicate these WAN connections that traverse over ISP networks. The magenta links connect global WAN's to DC metropolitan areas, which typically are responsible for the last miles of network distribution. Within the metropolitan area, there maybe one or more DC sites, only two are shown for clarity in the figure.

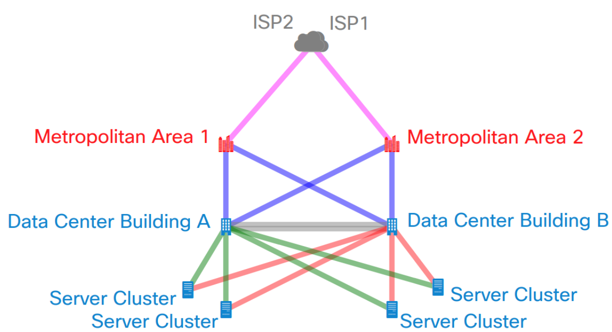


Figure 2.1: Generic Data Center Network Topology. The demarcation between the WAN and the LAN occurs at the Server Clusters. All the equipment with-in a cluster communicate over the LAN. Cluster to cluster communication, whether in the same building or across remote buildings occur over the WAN.

From a business perspective, the data center construction spending is estimated to reach $89 billion by 2027. The estimate nearly doubles the spend seen in 2018 [32]. At the core, the demands for DCs is driven by the expected consumer traffic to its services. With this much value at stake, capital and operational decisions must be based on robust system level models that couple IT traffic and DC designs.

The business and operational dependencies of network traffic to building loads as discussed above motivate this work. The work couples IT demands with building level resource utilization by first developing a simulator to demonstrate a method for geographically correlating five DCs with the incoming visits from a global user base using a minimum cost function. The resulting correlations are further extended to provide a forecast of the traffic. The generated traffic profile from the network simulator is interactively coupled used with EnergyPlus to reset the IT load at each time-step.

The contribution of this research is two-fold. First, it demonstrates a way to reason about network traffic profiles by developing a network simulator based on abstract usage data for a global internet service. Second, it validates that DC operators and designers can model future demands of building infrastructure systems and perform scenario models based the predicative characteristics of network traffic.

2.3 Literature Reviews

EnergyPlus, the US Department of Energy's building energy modeling software has supported DC modeling since release 8.3 [4]. The EnergyPlus modeling capability allows for IT equipment load schedules to be explicitly modeled in it. Today, EnergyPlus comes with three example DC models, in the form EnergyPlus Input Files (IDF). These IDFs provide a template that energy analysts can extend and augment to represent their specific DC designs. These default templates are hermetic and lack coordination with dynamic workloads that are prevalent in data centers. Dynamic behaviors of various internet applications inside DCs is presented by Harhol-Balter in [24]. However, there are proven techniques to integrate the dynamic behavior of DCs in EnergyPlus with supplemental software applications that allow for an interactive feedback loop with it. Building Control Virtual Test Bed (BCVTB) is one such application [33].

Wei demonstrates the use of BCVBT for modeling a mixed used facility that has a DC collocated with occupied spaces in [34]. Zhang demonstrated the use of BCVTB for the control of an educational building [35]. Zhang published their Python code base to allow others to replicate their work. Functionally, BCVTB creates an interactive process loop with EnergyPlus allowing the Python program to be aware of EnergyPlus simulations at every simulation time step. Figure 2.2 illustrates the interactive loop between EnergyPlus and a Python software agent that is implemented in the developed module of this work. In the next paragraph, background about WAN from an internet service perspective is provided.

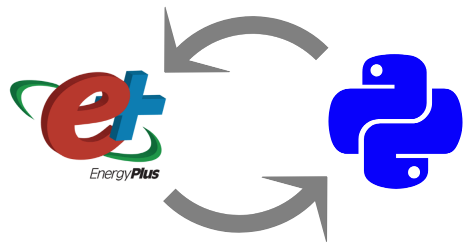


Figure 2.2: General process flow between EnergyPlus and internet traffic simulation. .

WANs serve as the backbone for many internet applications that operate across regionally distributed DCs. The traffic on WAN links are segregated into three classes; interactive, large file transfers, and background. LinkedIn's experience with these three classes of traffic is document well by Zhuang [36]. Interactive traffic consists of blocking operations, where the sequential byte level transactions are required to keep things proceeding. Large file transfers entail transmission of requested resources by an explicit deadline. An example of a deadline based application is a data transfer required for a status report that must be generated a particular time. Background traffic are workloads that are ok with opportunistic network availability and are resilient to any idempotent side effects in case the traffic gets preempted due to higher priority traffic. These three classes of traffic can either be user facing or back-end. Microsoft and Google have both published their experiences in designing and operating these massive global networks [37, 38].

2.4 Methodology

In this section the methods for characterising network traffic and correlating it with DC workloads is described. First, three step-wise methods that support the development of a network traffic simulator are presented. Namely these methods are:

1. The selection of a service level data-set that can characterize a global scale internet platform with a dispersed user base and geographically distributed data centers.

2. Abstraction of the service level information to map its network traffic to one of the data centers in the network,

3. A method to scale historical service demands into projections of future workloads for the DCs.

2.4.1 Selection criteria for selecting the global service to model

Below are the key criteria that was set for a representative global scale service:

1. High resolution usage data publicly available.

2. Non-Proprietary and acceptable for publications.

3. A service with global user base.

4. Representative of a distributed service with geographically dispersed data centers.

5. Publicly available data on physical infrastructure.

For the purposes of this research as a prototype model, Wikipedia.com was found to meet the entire list of the set criteria. First, a high resolution usage data-set was publicly available through a Kaggle.com forecasting competition [39]. The second criteria was satisfied by Wikipedia's source code and infrastructure design being free and open under MediaWiki copyright terms [40]. The obtained Wikipedia data-set represented seven natural languages. With naive association of the natural languages to the countries that they are the official national language, the data-set met the second criteria for a global user base. For compliance with the fifth criteria, Wikipedia's engineering site validated it's geographically dispersed DC infrastructure [41]. Given the free and open copy right terms, several key infrastructure attributes for Wikipedia data centers are readily available on the internet, meeting the fifth criteria.

2.4.2 Service Level Abstraction

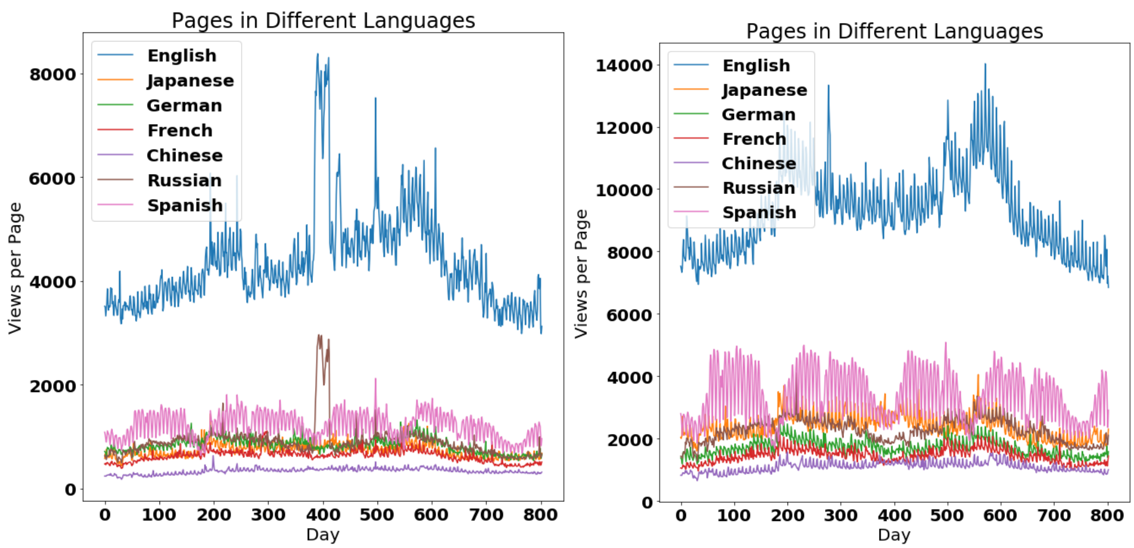
Meta information and statistical attributes of the Kaggle data-set has been used to develop the network simulator presented in this work. The data-set included traffic in counts of daily visits to 145,063 Wikipedia Pages for 803 days from July 2015 through September 2017. The data is partitioned differently for training and testing the predictive models. The training set is inclusive of traffic from July 2015 to December 2016. The remaining data is used to test the accuracy of the models.

All pages are segregated into 7 different languages. Namely the languages are English, Japanese, German, French, Chinese, Russian, and Spanish. Each page's natural language is extracted from the meta information embedded in the URL strings that are included with the original data-set. As an example, consider the URL string below.

```
1918_flu_pandemic_en.wikipedia.org_desktop_all-agents
```

The regular expression pattern search command re.search('[a-z][a-z].wikipedia.org',page) is used to extract the language meta data. For the example URL, regular expression search returned 'en' for English. For each language, the mean volume of visits per language is shown in 2.3a and the 95th quantile is shown in 2.3b.

The curves in Figure 2.3a and Figure 2.3b are indicative of the distribution of daily visits for each of the seven languages found in the data-set. For example, the 95th quantile represents pages that had more visits than 95% of the pages in the particular language on a given day. In the figure, the y-axis indicates the count of visits on the corresponding day noted on the x-axis. While the average curves indicate the average number visits to pages in the respective language on the corresponding day. Both of these curves can be used in the design phase of the DC buildings, with the 95 quantile determining the capacity and the average values supporting operational models. In this article, the average value is used as the indicator of the operational network model.



(a) Mean Value of Page Views

(b) 95^{th} Quantile Value of Page Views

Figure 2.3: Pages Views for Each Language

After segregation of the pages by language and dropping pages without language indicators, the languages are mapped to countries in which they are the official language. Figure 2.4 shows the mapping of languages to their respective countries by color groups; English (blue), Japanese (navy blue), German (gray), French (red), Chinese (light green), Russian (forest green), and Spanish (cyan). Red markers indicate the locations of Wikipedia DCs from around the world as listed in Table 2.1.

DC	English	Japanese	German	French	Chinese	French	Spanish	Total
Ashburn (ASH)	18	-	-	5	-	-	8	31
Carrollton (CAR)	2	-	-	-	-	-	11	13
Haarlem (AMS)	17	-	4	16	-	-	1	38
San Francisco (SFO)	3	-	-	1	-	-	-	4
Singapore (SIN)	9	1	-	4	5	1	-	20

Table 2.1: Languages to Ingress Sites. Data Center locations are obtained from [41]

Throughout this research these Wikipedia DCs are used to the model the network based on publicly available information. Several additional assumptions are made in regard to the attributes of the system that are not in the public domain. Furthermore, some of the system complexity is reduced for brevity. For example, the traffic generating

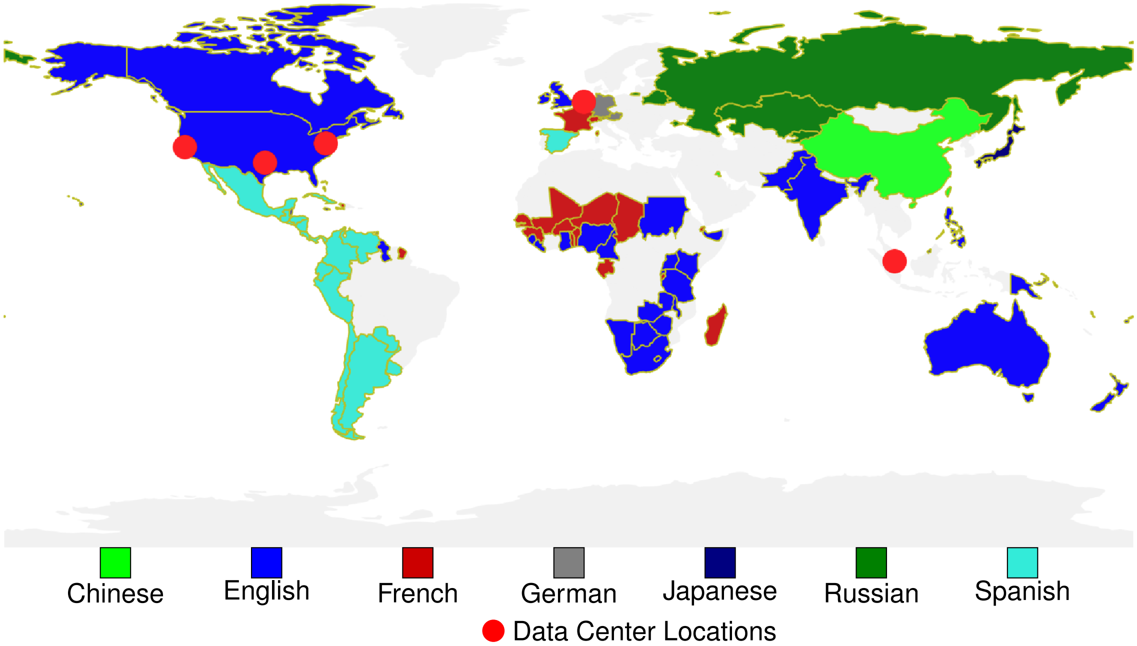


Figure 2.4: Source country of language and DC locations map.

in a particular country is allocated with their closest ingress points as listed in Table 2.1 by using a minimum distance function between the respective geographical codes.

The specific step-wise approach of mapping languages to the respective DC is shown in Table 2.2. Following these steps, Figure 2.5 shows that English is the most dominant language, with its traces appearing at all of Wikipedia's ingress sites while originating in 49 countries.

Step	Description
Step 1:	Map language to page by parsing URL structure.
Step 2:	Map languages to countries where they are the first tongue.
Step 3:	Map ingress sites to countries with minimum distance function.
Step 4:	Get the distribution of the number of countries served by each ingress site.
Step 5:	For each ingress site; sum up the daily views of pages in all language.

Table 2.2: Method for Traffic Allocation to each ingress site

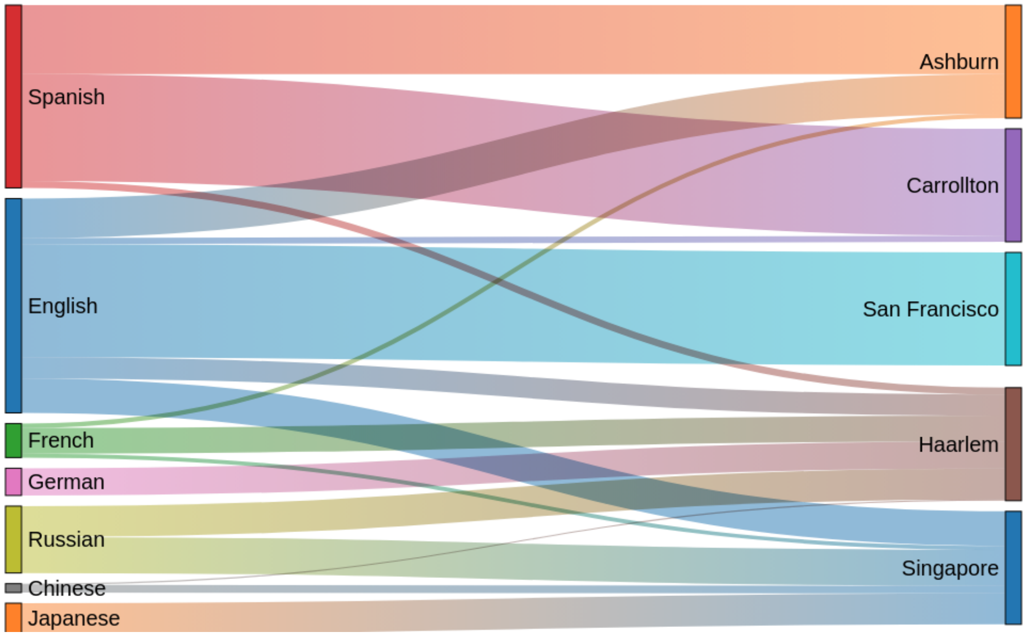


Figure 2.5: Language to data center flows. The thickness of the links at each data center site indicate the relative portion of traffic that the respective language demands at the data center.

2.4.3 Scaling service demands into the future

In this section, the Wikipedia traffic profiles are used to forecast future demands. Note that the traffic data is slightly modified to represent digital bits (instead of visit counts) in order to demonstrate another useful insight that network traffic inherently provides. The objective here is to determine the future service demands that drive workloads at each DC. To obtain the digital payload of the pages, their contents are converted to byte (8-bits) size representation. The bit size distribution of Wikipedia articles was not readily available in the public domain so an estimation method was developed for this work. First, several resources were consulted to determine the page size [42, 43]. The resulting page sizes for each of the seven languages studied in this article are noted in Table 2.3.

With the bit wise representation from Table 2.3, the time series of the traffic can be analyzed to make future predictions. The time series (t) dependencies of a variable X can generally be decomposed in trending (T), seasonal (S), and random (R) components, as

ID	Language	Count Pages	Word_{length}	Words_{page}	$\text{Bytes}_{character}$	Bytes_{page}	bits_{page}
zh	Mandarin	17229	1.0	1032	2	2064.0	16512.0
fr	French	17802	10.9	640	1	6976.0	55808.0
en	English	24108	8.23	640	1	5267.2	42137.6
ru	Russian	15022	9.97	640	1	6380.8	51046.4
de	German	18547	11.66	640	1	7462.4	59699.2
ja	Japanese	20431	1.0	1600	2	3200.0	25600.0
es	Spanish	14069	8.8	640	1	5632.0	45056.0

Table 2.3: Language to Page Size Classification

shown in Equation 2.1 [36].

$$X_t = T_t + S_t + R_t \tag{2.1}$$

More specifically T exists when there is a gradual shift across time, S indicates cyclic patterns, and R accounts for randomness.

In the next few paragraphs two forecasting methods that decompose the time-series into these three components are presented and their implementations along with their results are discussed. Namely these methods are:

1. The Auto Regressive Integrated Moving Average *(ARIMA)*, an open source statistical forecasting software suite [44].

2. As an alternate to ARIMA, Generalized Additive Model (GAM) is a proven method to forecast internet traffic. Specifically Facebook's *Prophet* implementation of GAM is implemented [45].

ARIMA Model: First, time-series analysis is performed using the Auto Regressive Integrated Moving Average (ARIMA) model. The auto regression component leverages the dependencies between an observation and some lagged time step. The integration component differentiates the raw observations from preceding time steps to make the series stationary. The moving average component quantifies the dependency between observations and residual errors with a moving average model applied to lagged observations. Each of the three components are specified as a model input parameter in the form ARIMA(p, d, q). The parameter p indicates the lag order, d indicates the degree of difference (i.e. subtract the previous value from the current value), and q indicates the size of the moving window (the moving average) [46].

The ARIMA model has been used effectively in previous literature to forecast 21 days of network traffic with 42 days of past trends [36]. This research extends the forecast out to 9 months using 18 months of past trends. The resulting output from ARIMA are shown in Figure 2.6. Figure 2.6's legend indicates the use of combination of ARIMA(2,1,2) and ARIMA(1,2,4) as parametric arguments to the ARIMA module. The lighter curves indicate ARIMA's predicated values and the darker curves indicate real data that was held back as the 'testing partition' described earlier. These results indicate that ARIMA can produce reasonable forecasts over a time horizon that may be conducive for DC design and operational decisions.

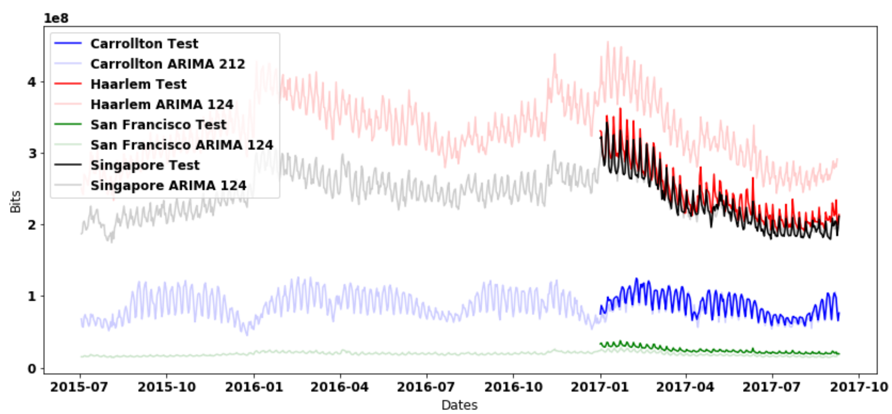
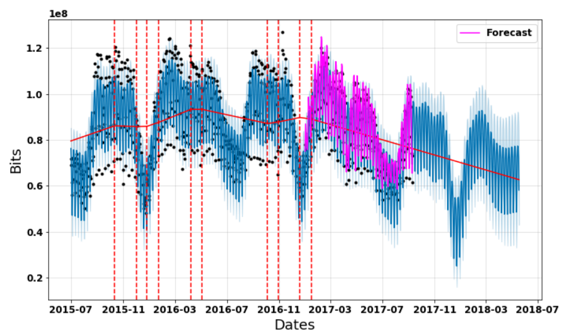


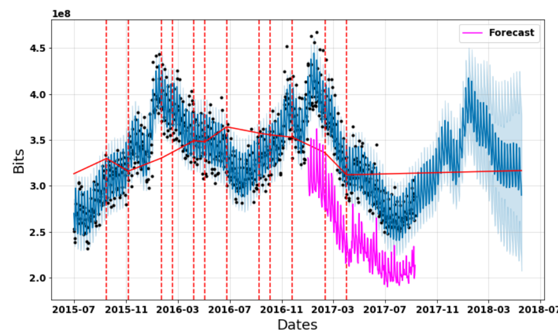
Figure 2.6: ARIMA Models: Historical trends and future projections.

Generalized Additive Model: Next, a variant of the generalized additive model (GAM) was simulated with the same bit wise time series as used in the ARIMA simulations. The model is explained in great detail by Taylor in [45]. The GAM model variant, Prophet, has a decomposable time series formulation similar to the time series dependence indicated in Equation 2.1. However, Prophet is supplemented with a term that accounts for holidays that occur at idiosyncratic intervals.

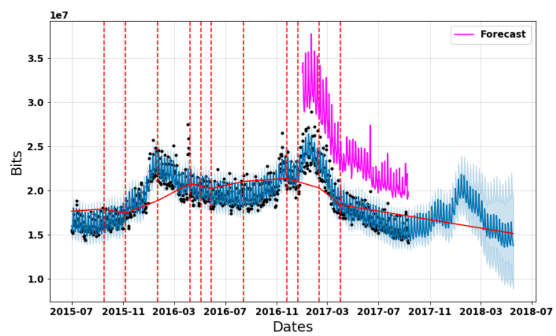
Furthermore, Prophet has a novel concept that deals with trends in forecast uncertainty, in that it uses a Laplace transform to randomly distribute future change points in the trend based on past data [45]. This can be seen by how closely the forecasts (blue lines) track the historical data (black dots) and the actual forecast based on the test data (magenta lines) in Figures 2.7a, 2.7b, 2.7c, 2.7d. The change point parameter is set to 0.3 and the yearly seasonality parameter is set to $True$ for these simulations. The forecast extends beyond the test data range which shows that the cone of uncertainty increases as the forecast is extended out further, indicated by the light blue curves.



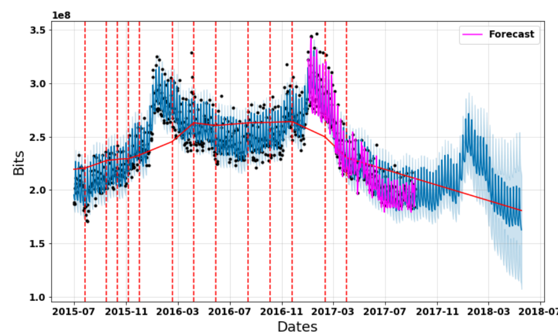
(a) Carrollton (DFW)



(b) Haarlem (AMS)



(c) San Francisco (SFO)



(d) Singapore (SIN)

Figure 2.7: Prophet Historical Trends, Test Validation and Traffic Forecast

Table 2.4 provides a comparison of the mean absolute error (MAPE) for four DC sites. The difference in error rates varies by a factor of 1.72 (for SIN) and over 52 (for SFO). Overall, in comparison it is shown that the Prophet model is superior to the ARIMA model in terms of accuracy of its predications.

DC ID	ARIMA	Prophet
AMS	2.35	0.058
DFW	8.16	1.22
SIN	2.57	1.47
SFO	32.2	0.619

Table 2.4: Mean Absolute Percentage Error

2.5 Results

In this section the results from using the traffic coefficients is presented. Following the steps listed in Table 2.2 yields the curves indicated in Figure 2.8. Each curve in the figure is inclusive of all the languages that are routed to the respective data cent.

To reason about these curves, recollect the distribution of the languages at each DC from Table 2.1. For example, the curve for San Francisco (SFO) in Figure 2.8 is nearly 100 times smaller than the curve for the Haarlem (AMS) site. This is due to only four countries being routed to San Francisco (the US is routed to Carrolton by the method used), whereas Haarlem has traffic routed from 38 countries. This naive approach evenly apportions the total count of the language's page visits equally to all countries in which it is the national language, regardless factors such as population or size.

Figure 2.9 shows the resulting CPU power profile for the English languages pages when using their traffic coefficients in EnergyPlus simulations for the five DCs. The coefficients are based on the average page view values from Figure 2.3a. The details of the EnergyPlus configuration are provided by Kumar in [47, 48]. Since the English language is the dominate language at the San Francisco site nearly all of the CPU resources at the site are dedicated to it. The constant load profile for San Francisco can be attributed to the corresponding flat curve shown in Figure 2.8.

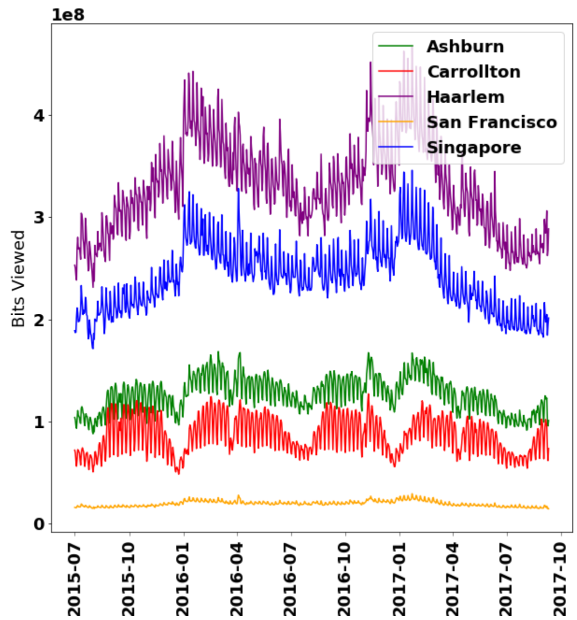


Figure 2.8: Total Traffic to Each Site after mapping.

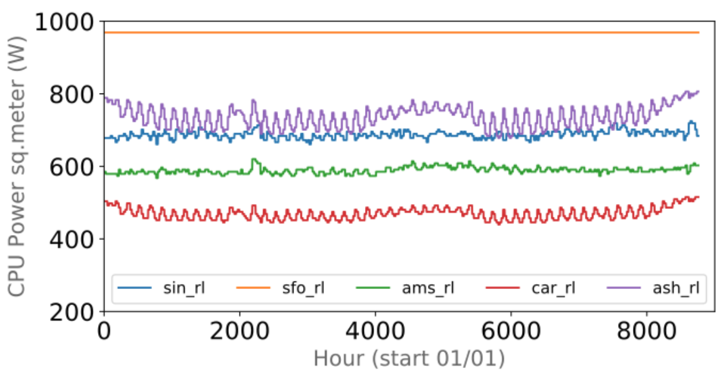


Figure 2.9: Plot of EnergyPlus CPU Profiles with the Network Coefficients .

2.6 Conclusion

The methods used in this chapter are indicative of a process that requires DC designers to first understand functional requirements of their distributed software systems. Once the underlying services are understood they need to be characterized by their geographical boundaries as done in the Service Level Abstraction section. In this study, languages are analogous to traditional internet services and the count of page views are used as the sole usage metric. Once the service boundaries are established, correlations between the physical resource dimensions can be configured as done in the EnergyPlus model discussed in the Results section. Specifically in this work, WANs were correlated to power demands at the DCs. The conversion of a network demands to power translates intrinsic software service attributes into a unit of measure that is more intuitive for building energy analysts and DC building designers. The presented service abstraction method only serves as proof of concept, service specific models are required to make this strategy effective. An example of the service specific model is shown in [36].

DC designers can use network profiles to implement energy models which assess their design choices at a single site or global level. At a single site level the building system components can be matched better with real demands. For example, if a service's demand is at a low point on cool winter night, the cooling plant's operating parameters just need to meet that low utilization point as opposed meeting the peak IT loads on the summer design day condition. This fine grained coupling may potentially lower the capital costs of the equipment at design time (if there is high confidence that peak traffic will not occur on the summer design day). In addition to capital savings, the network aware building systems can also supplement continuous load balancing strategies that optimize the total system by over subscribing the IT loads. Over subscription is feasible during part load conditions when the headroom in the electrical infrastructure can be exploited. Future work should look at a dynamic feedback loops to optimize network load balancing strategies and building controls.

Chapter 3

Building Energy Model of DCs

Abstract

Expressing site-specific load profiles and hardware specifications that reflect the information technology (IT) processes inside data centers have always been a challenge to do either benchmarks of building energy performance or predictive controls. As a substitute, data center building models usually assume naive hour-day-week schedules that don't align simulated operations with the weather profiles. This paper demonstrates a method towards using more representative load profiles in data center energy models by deriving the profiles based on global usage patterns of an internet platform. It is the first attempt to illustrate the coupling of an external signal with EnergyPlus as an indicator of IT load in a data center.

3.2 Introduction

This paper describes a data center (DC) building energy simulation framework. The framework is based on EnergyPlus as the physical model of the building operations and an externally implemented network traffic schedule as an indicator of the IT load. Namely, the target applications for these frameworks are the hyper-scale facilities that house global services such as social networks and search engines. For this class of facilities, the significance of network traffic to DC operations is exemplified by the sudden change in peoples internet usage behaviors due to the COVID-19 pandemic. Through the pandemic, DCs across the globe have seen a disruptive shift in user traffic patterns that were not known just weeks prior to the first stay-in-place orders. Given this timely example, it is imperative that DC operators be able to simulate their facilities to verify that their infrastructure can handle these types of shifts in traffic. However, presently there is a lack of publicly available information about how to build such simulations.

The contribution of this work is two-fold. First, it provides a demonstration for characterizing data centers and IT equipment in EnergyPlus. Second, by deriving the workload profile from network traffic, this work provides a perspective for reasoning about temporal profiles of the workloads that hyper-scale data centers must support.

DCs have 10 times the power density of conventional buildings. With this density, it is essential that during the design phase designers have access to representative building energy models to size equipment and to validate jurisdictional compliance. However, these building energy models are typically put on the shelf once the facility is turned over to the operational teams. With much of the life cycle costs of a data center attributed to the use-phase, having building energy models that represent the cyber-physical dynamics of their facility can be valuable to support operational decisions too.

In this work, wide area network traffic bandwidth is demonstrated as a proxy for IT loads in data center buildings. However, any technique that characterizes a fine grain coupling between the IT workloads and the building systems would be valuable for hyper-scale DCs running online platforms such as social media sites, search engines, or public cloud services. These platforms are typically distributed through out the world for redundancy and performance objectives for their global user base. In terms of building scale, each data center can scale beyond a hundred thousand square meters with 100s of MW of power. Even with the ever growing needs for hyper-scale data centers today, there is a lack of publicly available literature which discuss coupling building energy models with IT operations to help operators reason about actual service workloads and their building's performance

In the recent past, the power usage effectiveness metric (PUE) as defined by Equation 4.1 has been a key performance indicator for DC facilities architects and facilities operators.

$$PUE = \frac{E_{total}}{E_{IT}} \tag{3.1}$$

E_{total} = Total Power Used at Facility

E_{IT} = Power Consumed by IT Equipment

The PUE is a intuitive metric to reason about. In consideration of the PUE, the mechanical inefficiencies and electrical distribution losses external to the IT equipment contribute to the difference between the numerator and denominator of Equation 4.1. In operations, the facilities and IT parameters change simultaneously together in a continuous sequence, lending to accurate real time evaluations. However, the continuous states of IT workloads and ambient environmental conditions makes design time PUE calculations complicated. The complications drive DC building designers to evaluate the efficiency metric, by averaging discrete step-wise (hour-day-week) workload values and taking the worst case values to benchmark the facility.

However, without accounting for continuous workload profiles these coarse models misrepresent the part-load operations of the DC and inaccurately quantify total energy demands over a time period. The misrepresentation has significant impacts throughout the life of the hardware deployed in these DC facilities. For example without realistic coincident alignment of workloads and ambient conditions, thermo-electric equipment whose energy use is dependent on workloads and ambient temperatures may be over-sized for significant portions of their operational times. Yet, during these times the equipment are still allocated their nameplate power draws regardless of their lower operational points. The allocation translates to power being reserved regardless of real demand.

The simulations demonstrated in this research allow for more realistic evaluations of DC energy use. These more realistic evaluations are useful for two things. First, operators can use the realistic cyber-phsyical models to simulate the DC building performance under perceived usage changes. Second, by exposing the facility's power and cooling equipment headroom for non-design day conditions they can enable DC operators to opportunistically oversubscribe the IT loads. Such a oversubscribing scheme can be implemented by extending the electrical over-subscription leading to free capacity schemes presented by Li Li18 when coupled with predicative modeling techniques.

The contribution of this work is the demonstration of an IT load aware building energy model that integrates an external Python script to dynamically reset the IT load that must be cooled within EnergyPlus. The rest of the paper discusses specific modules that one of the authors built to couple the building systems and IT.

In the next section, similar works on data center energy models are discussed. In the subsequent section, Methodology, the methods and reasoning behind the modules developed in this work are discussed. The results from implementing these methods are then presented in the Results section followed by a Discussion section in which the authors reason about the article's results and claims. The paper then concludes by highlighting the contribution and identifying opportunities for extending this work.

3.3 Similar Works

As described above, PUE is not the comprehensive metric for DC energy efficiency. By acknowledging that PUE does not account for IT equipment efficiency, Perolini provides a coordinated control strategy across IT workload and building infrastructure based on network queuing theory parolini12. Perolini logically composes a set of IT systems and supporting infrastructure as a singular cyber physical system network graph. Hierarchically structured quality of service (QoS) values is common among Perolini and Li, who uses the QoS to optimize IT performance in terms of the power distribution system Li18.

Both authors dynamically tune IT with the facilities infrastructure systems. In terms of exploiting the QoS, the fundamental difference between these two works is that Li considers the IT workload as the controlled variable bound by the facility's power distribution systems and Perolini considers the cooling equipment as the controlled variable bound by the IT workload. In their recognition of lower QoS DC workloads as being preemption tolerant and higher QoS as time sensitive workloads; these methods allow over-subscription of power and thermal capacities without any service level performance degradation.

DC cooling systems have been algorithmically coupled with DC IT workloads by Wei in wei17. They use a reinforcement learning agent that is aware of the DC's thermal state in real-time. The agent acts as a controller of the HVAC equipment and respective IT traffic balancer, where the balancer migrates work between two or more DCs. In the work they demonstrated that when given a state-action pair and an objective function, the agent takes a control action in a given state to reduce power while allowing the IT system to meet it's performance objective in terms of processing latency. The state-action pairs are optimized with an objective function that values the power demand along with a IT performance metric at a given time-step. Wei's work was limited to DCs located in mixed use buildings, where the cooling system had some fungibility with other parts of the building, allowing waste energy from the DC to be reclaimed to heat the other parts. Nonetheless, their work is similar to this research in that it also integrated EnergyPlus together with Python.

3.4 Methodology

In this section a dynamic workload-profile based energy simulator is introduced and the simulation is described in detail. First, an overview of this work's cross platform software integration is presented. Then details about each of the two main components, namely EnergyPlus and Python based traffic models, are discussed. As shown in Figure 3.1, the proposed simulator uses Python to reset the DC IT load for each time-step. In the subsequent modeling time-step, the EnergyPlus models run with the externally revised variables. The basic process loop of the simulator is illustrated in Figure 3.2.

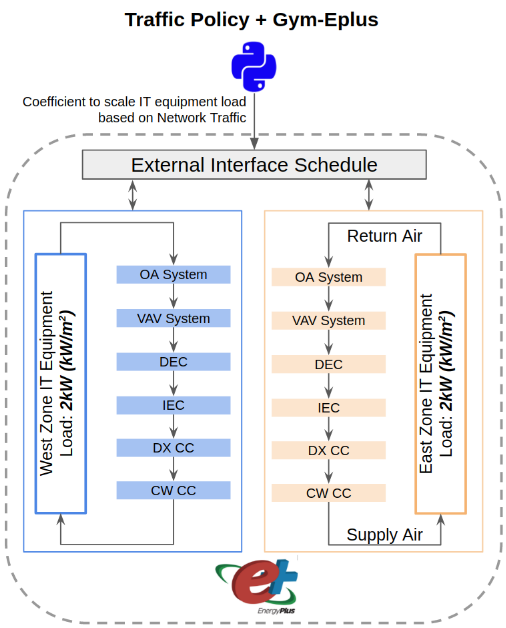


Figure 3.1: EnergyPlus and Traffic Model.

The simulator integrates algorithms that are aware of network traffic profiles programmed in Python with EnergyPlus through the Building Controls Virtual Test Bed (BCVTB) wetter16. The BCVTB interface from Gym-EPlus zhang19 is used to implement the interaction. This work extends Gym-Eplus capability by making it reset the IT load in DCs in addition to its thermal reset features. DCs have been explicitly supported in EnergyPlus since Version 8.3.0. Using the already supported DC variable for CPU load schedules in EnergyPlus, the xml file configuration as shown in Figure 3.3 couples the Python module

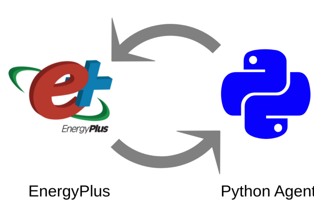


Figure 3.2: Dynamic Process Flow between EnergyPlus and the Python Agent.

with EnergyPlus.

```
<?xml version="1.0" encoding="ISO-8859-1"?>
<!DOCTYPE BCVTB-variables SYSTEM "variables.dtd">

<BCVTB-variables>

<!-- Recieve from E+ -->
  <variable source="EnergyPlus">
   <EnergyPlus name="East Zone" type="Zone Thermostat Heating Setpoint Temperature"/>
  </variable>

  <variable source="EnergyPlus">
   <EnergyPlus name="East Zone" type="Zone Thermostat Cooling Setpoint Temperature"/>
  </variable>

  <variable source="EnergyPlus">
   <EnergyPlus name="Whole Building" type="Facility Total Building Electric Demand Power"/>
  </variable>

  <variable source="EnergyPlus">
   <EnergyPlus name="Whole Building" type="Facility Total Electric Demand Power"/>
  </variable>

  <variable source="EnergyPlus">
   <EnergyPlus name="Whole Building" type="Facility Total HVAC Electric Demand Power"/>
  </variable>


<!-- Send to E+ -->
 <variable source="Ptolemy">
   <EnergyPlus schedule="HeatingSetPoint_RL"/>
 </variable>

 <variable source="Ptolemy">
   <EnergyPlus schedule="CoolingSetPoint_RL"/>
 </variable>

 <variable source="Ptolemy">
   <EnergyPlus schedule="Data Center CPU Loading Schedule_RL"/>
 </variable>

</BCVTB-variables>
```

Figure 3.3: EnergyPlus variables.cfg used to integrate Python and EnergyPlus. Other variable maps from GymEplus are listed in the variable.cfg, but not used in these simulations.

The baseline EnergyPlus model of the data center is adapted from Moriyama moriyama18. Moriyama's building shell consists of two data center rooms. The first room, the West Zone is 232 square meters and the second room, East Zone, is 259 square meters. Each data center room has dedicated mechanical and electrical equipment that are symmetrical to each other. Throughout the simulations the building envelope, mechanical, and electrical modeling objects are not modified from the baseline. However, for this research, as the goal is to represent hyper-scale DCs; the IT equipment objects are changed to closer resemble the current practices in this class of DCs based on one of the author's industrial experience.

Three statically configured changes are made to the baseline model's ITE object.

Namely the changes include the values for server inlet temperature, fan power ratio compared relative to the overall server power, and the CPU power density fields are changed. The typical EnergyPlus ITE object for each zone is provided in Figure 3.4. First on line 16, the server entering air temperature is changed to $25°C$ from $15°C$. Second, on line 12 the fan power fraction is changed to 0.10 from 0.40. The last static variable change increases the load density of the data center to 2 $\frac{kW/m^2}{}$ from 0.2 $\frac{kW/m^2}{}$ on line 8. Details on how this power density was derived is provided later in Algorithm 1.

```
1   ElectricEquipment:ITE:AirCooled,
2     WestDataCenter_Equip,        !- Name
3     West Zone,                   !- Zone Name
4     FlowControlWithApproachTemperatures, !- FC *
5     Watts/Area,                  !- P Calc. Method
6     ,                            !- {W}
7     ,                            !- Number of Units
8     2000,                        !-  {W/m2}
9     Data Center Operation Schedule,  !- Power Sch.
10    Data Center CPU Loading Schedule_RL,  !- cpuSch.
11    Data Center Servers Power fLoadTemp,  !-
12    0.1,                         !- Fan Power Input
13    0.0001,                      !- AFR  {m3/s-W}
14    Data Center Servers Airflow fLoadTemp,  !-
15    ECM FanPower fFlow,          !- fan Flow
16    25,                          !- EAT {C}
17    A3,                          !- ASHRAE Class
18    AdjustedSupply,              !-Inlet Connection
19    ,                            !- Room Air Model
20    ,                            !- Room Air Model
21    West Zone Inlet Node,        !- SA
22    0.1,                         !- Recric. Ratio
23    Data Center Recirculation fLoadTemp,  !-
24    0.97,                         !- PSU efficiency
25    UPS Efficiency fPLR,         !- UPS PLR Curve
26    1,                           !- PS Losses to Zone
27    ITE-CPU,                     !- CPU End-Use
28    ITE-Fans,                    !- Fan End-Use
29    ITE-UPS,                     !- PS End-Use
30    2,                           !- SAT *
31    ,                            !- SAT Schedule *
32    -2,                          !- RAT *
33    ;                            !- RAT Schedule *
```

Figure 3.4: EnergyPlus ITE Object Defintion. New features of EnergyPlus 8.9 are denoted with *.

The only dynamic variable change to the ITE object definition specifies the dynamic CPU Loading Schedule_RL on line 10 of Figure 3.4. This new schedule replaces the original schedule, CPU Loading Schedule. Both of these schedules are shown in the IDF snippet in Figure 3.5. The CPU Loading Schedule_RL is called from the IDF as an external interface through the BCVTB. For the BCVTB and EnergyPlus interface, this new schedule is mapped between the two software platforms in the variable.cfg file on line 38. Then at each time-step, a value for the CPU load is passed from Python to EnergyPlus.

The passed value is multiplied by the CPU power density from line 8 of Figure 3.4 for the simulation time-step.

```
Schedule:Compact,
  Data Center CPU Loading Schedule,   !- Name
  Any Number,                    !- Schedule Type Limits Name
  Through: 12/31,                !- Field 1
  For: SummerDesignDay,          !- Field 2
  Until: 24:00,1.00,             !- Field 3
  For: AllOtherDays,             !- Field 5
  Until: 6:00,0.50,              !- Field 6
  Until: 8:00,0.75,              !- Field 8
  Until: 18:00,1.00,             !- Field 10
  Until: 24:00,0.80;             !- Field 12

ExternalInterface:Schedule,
 Data Center CPU Loading Schedule_RL,   !- Name
  Any Number , !- ScheduleType
  0; !- Initial value, used during warm-up
```

Figure 3.5: EnergyPlus IT load reset schedule definitions. The Schedule: Compact is replaced with the schedule defined in the External Interface: Schedule.

There are two ways to input the IT power load into EnergyPlus. The first is the unit count and unit-power method. The second is the power-density method. As seen above the floor area density method is used for this work. The density method is more conducive to scaling with the building size than the unit-power method. Algorithm 1 indicates the steps used to translate the properties from an actual hyper-scale data center to Moriyama's model. The density (ρ) is simply the product of the total provisions power for the IT equipment on the server floor (P_f) and the total server floor area (A_F).

Although expressing the IT density as a constant value over the entire floor area suffices for EnergyPlus' view of the IT load as a lumped thermal parameter, it is a naive representation of the power distribution on the floor. In reality racks are not placed evenly across the entire server floor, but are placed in rectilinear arrangements, as represented by A_r in Algorithm 2 and illustrated in 3.6. By following the equations in Algorithm 1.3, the rack counts and rack unit densities can be obtained and the method of entry can be changed.

Now, the CPU Loading Schedule_RL as passed in from the Python program to EnergyPlus is described (also see 2). The basis for the schedule is a network traffic model built upon simulations of real world network traffic for a global service. The choice to

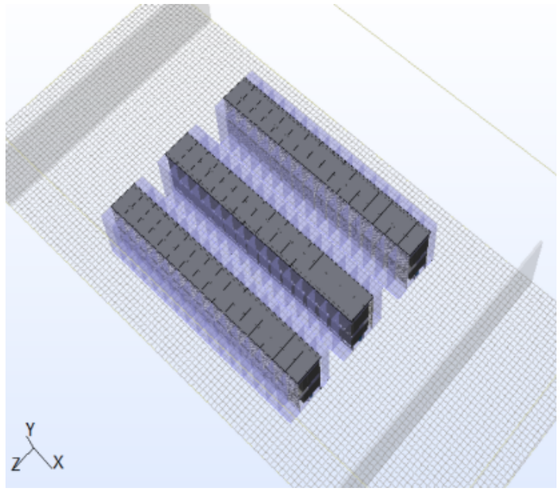


Figure 3.6: Server room layout. The gray elements in the figure are the hot aisles and the light purple elements are the server racks. The objective of the cited work was to determine the optimal spacing of adjacent racks across hot-aisles. Image from [29]

characterise the DC IT equipment load with bandwidth of network traffic is superior to the usual hour-day-week schedules as an operational model because:

1. Most DCs serve international users across many time zones (see discussion in Chapter 2).

2. The DC workloads are known to not be stable across time harchol13.

3. Network traffic is conducive to predicative models based around world events and seasons zhuang15.

Characterizing the traffic profile for an online service platform requires granular data that spans across a wide temporal range. However, due to the proprietary nature of the internet industry such data that allows for building level traffic profiles is not publicly available. Therefore, in this research a network traffic simulator is created. The objective for the simulator was to represent a globally distributed online platform indicative of real world user demand. To represent a global service, the load factors in this article reflect visits to 145,063 Wikipedia pages over an 18-month period as provided by Kaggle kaggle17. In

Algorithm 2 Rack Counts from Building and Power Properties

$\rho = \frac{P_f}{A_F}$
$A_r = A_f \times F_f$
$R_{\#} = \frac{A_r}{R_a}$
$P_{rs} = \frac{P_f \times (1 - F_n)}{R_{\#}}$
$P_{rn} = P_{rs} \times F_n$
$P_r = P_{rs} + P_{rn}$

Where:

ρ = Power Density of server floor. This value is used in the EnergyPlus Models.
A_f = Total floor area.
A_r = Area available for rack deployment.
R_a = Rack footprint area.
$R_{\#}$ = Rack count.
P_f = Provisioned power for IT for server floor.
P_{rs} = Power for rack server equipment.
P_{rn} = Power for rack network equipment.
P_r = Total power of rack.
F_f = Fraction of A_f that is deployable with Racks.
F_n = Fraction of power to rack allocated to network devices.

this work, publicly available information about Wikipedia's infrastructure establishes the geographical locations for the DCs as illustrated in the map in Figure 3.7.

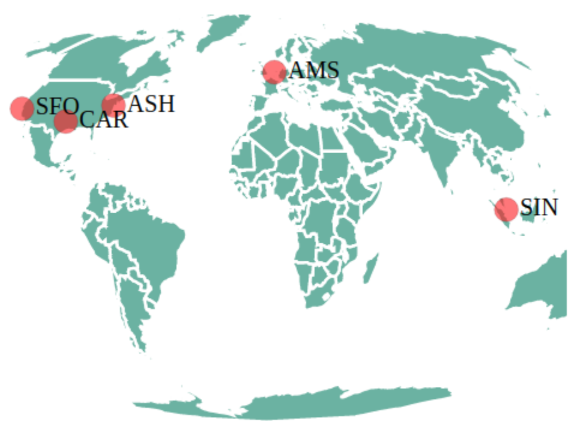


Figure 3.7: Data Center Locations Map. SFO: San Francisco, CAR: Carrolton, TX, ASH: Ashburn VA, AMS: Haarlem, Netherlands, SIN: Singpore.

One issue with the Kaggle data set is that it just provides a time series of page visits agnostic of source location (ie user location) or serving DC. For evaluating DC level workloads, the pages were mapped to a DC location as part of a pre-processing step of this research. The pre-processing required handling raw URL strings and parsing out it's language hash markers. Then, countries where these languages are the official languages are mapped to the nearest Wikipedia DC to indicate the traffic to each DC. The step-wise procedure is in indicated in Table 3.1.

Table 3.1: Steps for converting URL to traffic

Step 1:	Map language to page by parsing URL structure.
Step 2:	Map languages to countries where they are the first tongue.
Step 3:	Map ingress sites to countries with minimum distance function.
Step 4:	Get the distribution of the number of countries served by each ingress site.
Step 5:	For each ingress site; sum up the daily views of pages in all language.

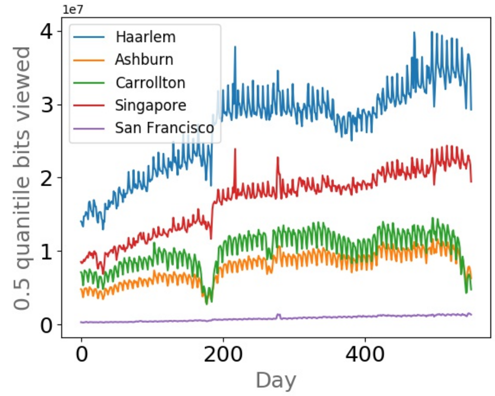
The procedure resulted in the seven languages being routed by a minimum distance function from any country that they are the official language to the nearest DC site. Treating each of the seven languages as a service provides an abstraction that makes each language an isolated platform.

Figure 3.8 shows curves with all languages to a particular data center aggregated together. These curves are translated to a coefficient that scales the IT load indicated on line 8 of Figure 3.4. The coefficients for each data center are normalized to the maximum traffic volume; i.e. max traffic indicates the upper bound with a coefficient of 1. These coefficients are independent across the five data centers.

Next we discuss the results from a model build with the methods discussed in this section.

3.5 Results

The traffic aware EnergyPlus models are simulated for each data center location through GymEplus in a batch process loop. In the batch workflow, the same IDF file is used



.

Figure 3.8: Sum of English, French, German, Mandarin, Spanish, Russian, and Japanese traffic to each of the 5 DC locations.

to represent all of the data centers shown on the map in Figure 3.7, except their local weather files are changed by the scripted loop. In these reset load (RL) simulations, at each time step the traffic load factor is pulled in from the Python program and is passed to EnergyPlus by BCTVB. This demonstrates that using an external interface (such as logic scripted in Python), building energy models can facilitate the analysis of a network of data centers in a single workflow.

A second set of simulations without the external interface (NoRL) were also run for each DC with a similar workflow to quantify the energy use with default CPU loading schedule shown in Figure 3.5. The total annualized energy use of the two models is plotted for comparison in Figure 3.9. The red bars indicate the simulations in which the CPU loads are reset at each time-step (RL), and the blue bars indicate simulations without interactive resetting of the loads (NoRL). For Singapore (sin), San Francisco (sfo), and Ashburn (ash) the RL simulations result in higher annualized energy compared to the NoRL model. While for Amsterdam (ams) and Carrolton, TX (car), the RL model results in lower energy demand compared to the statically configured load from the NoRL simulation.

The variations in the relative energy demands between the two models can be attributed to the CPU load profiles as illustrated in Figure 3.10. The figure illustrates the

Figure 3.9: Total Site annual energy for statically (NoRL) configured IT load and dynamically reset (RL) IT loads.

time series plot of each DC analyzed through the RL simulations with line curves. The x-axis indicates the hour of the year and the y-axis indicates the CPU load for each respective DC. The CPU profiles for each DC that their average values are distinct from one another. Carrolton and Ashburn appear to have noticeable seasonal patterns. Amsterdam and Singapore DCs show irregular oscillations in demand throughout the year, but have a tight band. The San Francisco DC has a constant line. This constant demand is due to the load not varying much from the peak capacity in the traffic profile that was used for the site.

In contrast to the distinct CPU load profiles of the RL loads as discussed above, with default schedule configuration of IT load profiles used in the NoRL models, the CPU loads at all of the DCs are identical to each other. The static property of the NoRL model is also indicated in Figure 3.10 by the gray band. The gray band is actually composed of line curves that cycle diurnally with the given schedule.

Figure 3.11 shows a stacked histogram for the set of DCs modeled. This plot shows that even with identical building systems the efficiency of each DC will vary across the globe. One major contributor to this difference is obviously the local weather conditions which DC operators can't control. However, the second contributor is the workloads at

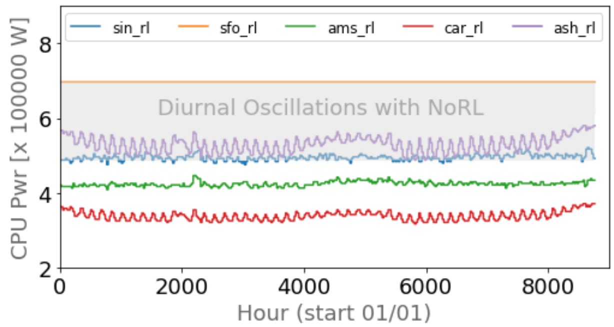


Figure 3.10: Time series of the total CPU power at each DC (see legend). Gray area indicates the daily demand cycle that the IT equipment creates with NoRL.

the DC. The workload is a variable that can be controlled by the DC operators.

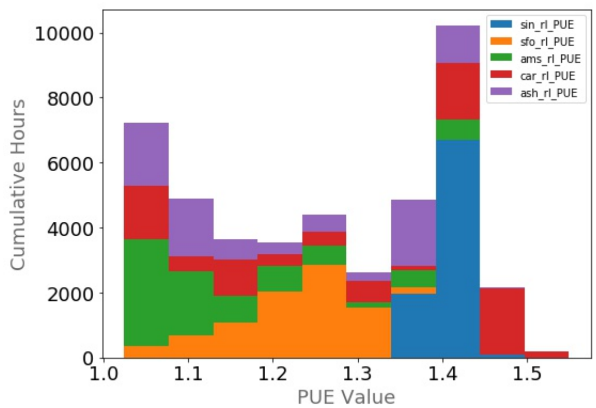


Figure 3.11: Stacked PUE Histogram for all five data centers .

In the next section, the extensibility of the traffic based building energy model towards predicative scenarios and the potential to use this framework to exploit 'free capacity' are discussed.

3.6 Discussion

One obstacle that building operators face when using building energy models to make operational decisions is that working with these models requires deep knowledge about their software implementation. Unlike conventional buildings, DC operators do control the IT loads therefore allowing the IT loads to characterized by external software for building energy models can allow operators to do some interesting things. For example, operations teams can simulate perceived future changes to their work loads. As mentioned above, predicative modeling is feasible when using network traffic as the proxy for IT loads kumar20, kumar20b, zhuang15. Network traffic has been shown to be predictable within reasonable accuracy for internet services by Linkedin in zhuang15. Figure 3.12 shows the predicative models for four of the data center studied in the simulations for this work.

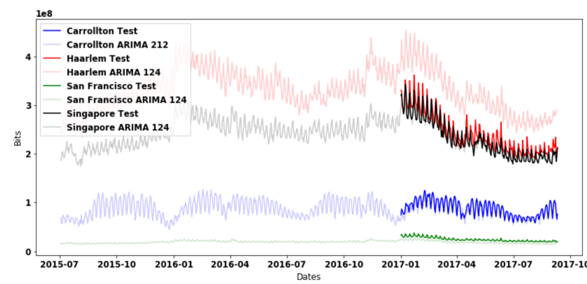


Figure 3.12: Forecasting Model of the Traffic.

In this research the network traffic serves as a proxy for CPU utilization. In practice the network traffic and CPU have complex correlations that can't be generalized with the presented approach. In production DC environments representative correlations can be obtained between network traffic, the IT workloads the traffic instantiates, and the workload's CPU demand. However, proving such correlations is out of scope of research. Nonetheless, every data center will be subject to its own traffic models due to it being an intrinsic property of the service.

This research assumes that all the facilities are of the same size in terms of power, space, and cooling. From looking at Figure 3.8, the San Francisco site has a much lower traffic profile than Haarlem. The claim that the same power capacity handles this range of traffic requires another assumption. This assumption is that the CPU-Network ratios vary from site to site. For example a bit of network traffic generates 40 times as much CPU workload in San Francisco as it does in Haarlem. This assumption is the basis for normalizing the traffic coefficient, as described by the discussions on Figure 3.8. This is a realistic condition in DC fleets which have different generations of IT hardware in operations at various DCs and one generation of hardware is way more efficient then the other for its specific work load. In practice this condition can also be encountered when software optimizations for specific workloads are done for targeted consumer markets that are geographically segregated. Nonetheless, since the network coefficient is bound between 0 and 1, any network-workload-CPU model can be supported in the same framework.

As an example of free capacity mentioned above, consider a design day dry-bulb temperature of 105°F. When a peak in IT workload occurs on a more favorable day, say 95°F, the computer room air conditioner heat rejection equipment needs only 50% of the designed power value liebert20. With a slight modification in the electrical infrastructure, this difference can opportunistically be allocated to IT workloads. However, slight the electrical modification, the decision is most cost effectively made during the design phase of the facility. This influence on the design presents a case for using the fine grained load aware models like done for cpu_load_reset in this work during the design phase as-well.

Opportunistically using 50% of the provisioned power from the cooling equipment to power the IT equipment requires some further insights about DC operation. The 50% claim is based on nameplate full load amps (FLA) for two different dry-coolers (Models D-466 and D-880) that are matched with a 105kW indoor computer room air conditioner (DC Model 105). One of the dry-coolers is rated at 95°F and the other is rated at 105°F liebert20. The FLA for these units are 14 Amps and 28 Amps respectively. Physically this the FLA values influences the breaker sizes, power wire sizes, utility power feed reservations, and back-up generator reservation decisions.

To summarize the last two paragraphs more explicitly, in conditions where the ambient enthalpy is lower than the design day, electrical provisions beyond the real-time demand relative to the design values are stranded. This is an important consideration for a building class where its utility is measured by the power delivered to IT equipment use. Anytime when the stranded power can be re-purposed from auxiliary infrastructure (such as chillers, cooling towers, and transformers) to the IT equipment, it leads to compelling return on investment cases.

3.7 Conclusion

There are two notable benefits of resetting the IT load values outside of the IDF file. First, defining load values for each hour in the IDF file is toilsome and error prone. The toil of entering values for each simulation time-step would require 8,760 entries in the file. This increases the chance of introducing errors into the simulation. Second, the external definition allows more sophisticated logic to control the time-step variables. In this article, only the IT load factors were reset, none-the-less the same interface can reset many other simulation run-parameters (Air temperature, chilled water temperatures, condenser water temperatures, and internal network bandwidth) with similar logic. An example of a feedback logic is reinforcement learning, which can be framed to globally optimize the systems and is an topic for future research.

The traffic profile used in this article are representative of a globally distributed service's user facing workloads and suffices for purposes of demonstrating the dynamics of DC operational loads. Each real-world service will have a unique profile resulting from a combination of critical and opportunistic back-end workloads. The modular construction of this model is conducive for incorporating the other workloads and being inclusive of back-end workloads as-well.

Figure 3.8 aggregates all the languages to provide an overall building simulation. Future work that need to assess a service platform can create multiple ITE objects in EnergyPlus and quantify the energy demands for each in isolation.

Chapter 4

Marginal Costs of Energy

4.1 Abstract

Over the last decade, operational efficiency optimizations in data center (DC) facilities designs have curtailed their absolute power demands. However, their physical footprint is still growing. This growth in capacity may offset the efficiency gains at best or may even increase the power demand in absolute terms. Such offsetting effects make system level life cycle environmental footprint evaluations complex for distributed services operating in these DCs.

To support system level evaluations for services operating in DCs, this research uses simulated network traffic profiles and coincident energy generation source aware building energy models (BEM) to evaluate the marginal carbon footprint of a globally spanning network of data centers. The result of this research is a prototype of a BEM based framework that can be used in environmental decisions to characterize DC life-cycle costs at internet service levels.

4.3 Introduction

Globally distributed internet services are ubiquitous today. These services are driving the demand to build mega-watt scale data center facilities (DC) distributed through out the globe. In a 2015 study data centers were forecast to consume as much as 13% of the global energy production by 2030 andrae15. More optimistic models form the US Department of Energy for the US showed a curtailment with up to fifty percent decline in energy compared to the industry's use of 2% of the power produced by the national grid in 2005 as a result of using state of the art efficiency and consolidation practices Shehabi16. As more and more parts of society are transitioning to data center dependent online paradigms, the absolute demand of data centers is growing. The volume of growth is exemplified by the capital costs being invested across the world in constructing these data centers.

The growth in data center capital construction costs will reach $89 billion by 2027, a significant increase from the $45 billion spent in 2018 dcmarket19. Capital costs aren't the only commitments for data center owners however. DC owner,s also incur significant operational costs throughout the entire operational lives of their facilities.

Over a 20-year life of a continuously operating data-center facility, the use-phase energy costs can exceed its capital costs while having a much larger ecological footprint. Given the accumulation of costs and impacts over the life of data centers, there is a need for a robust model the couples the information technology (IT) and building systems with their energy supply sources through its useful life. In this article a geographically extensible model that accounts for the workloads, building systems, and power utility grid is presented.

In the rest of this paper a model for coincident energy demand and marginal energy costs (MEC) of a set of data centers is proposed and developed. First, the proposed method uses a hybrid model consisting of EnergyPlus and Python programming modules as developed by the researcher in kumar20. For this article, the researcher's original hybrid model is modified as described in the methodology section to be more indicative of the current operations of cloud data centers. Then second, the resulting time series of operational energy demand profile is used as input to a Python based open source MEC simulation tool that is also extended as described in the methodology section.

The MEC calculations are based on the Dispatch Optimized Systems Cost of Energy (DOSCOE) model developed by Platt platt17. DOSCOE provides a linear programming platform that computes the monetary costs and several environmental emissions associated with operating a mix of dispatch-able and non-dispatch-able energy sources. In this context, dispatch-able energy sources are those that can be controlled to meet demand. Natural gas power plants are examples of dispatch-able sources of energy, where the plant operators can control the mass flow rates of the combustion gases to curtail generation rates. On the contrary are the non-dispatchable sources, where the energy generation is dependent on extrinsic factors. An example of non-dispatchable energy source is solar; where cloud cover greatly effects the generation rate and no power can be generated at night.

Modeling the costs for a mixture of dispatchable and non-dispatchable generators is complex as most non-dispatchable sources are only accounted for as opportunistic supply sources when sizing the power generation infrastructure. By design the dispatchable generators are sized to meet the full demand in a worst-case condition when no dispatchable power is available platt17. However, when non-dispatchable power is opportunistically available, it supplements the grid; allowing dispatchable sources to be turned down to part loads. This saves fuel costs for dispatchable sources (ie natural gas generators), but it leaves their physical infrastructure stranded and underutilized.

This research's coupling of the DOSCOE model with a BEM quantifies the monetary and ecological costs associated with operating data centers in grids with mixtures of energy sources bound by physical constraints. The developed model is evaluated by matching the marginal costs of energy with data center demands on hourly intervals. Furthermore, the resulting model is inclusive of the stranded costs of the underutilized power infrastructure.

In the next section, Background, informative context is provided to set the proper use-case for this framework. Then in the Similar Works section, past literature which have quantified the ecological life cycle cost of data centers and internet services are summarized. In the Methodology section, the two main modules of the software implementation of this research are presented. Specifically these modules are a modified version of hybrid building energy model and a novel MEC model based on DOSCOE. After the details of the models are presented, the results are discussed in the Results and Discussion section followed by the Conclusions.

4.4 Background

Data centers are critical to modern internet experiences for billions of people. They are the key enablers for disseminating information in real time regardless of people's location. As an example of location agnostic services geographical dispersed infrastructure, Figure 4.1 illustrates a geographically distributed architecture that enables data centers to provide globally consistent internet experience that have become the status quo over the last decade. Distributed software architectures implemented in the server clusters at the leaf-nodes consist of a collection of autonomous computing resources that appear to its users as a single coherent system tanenbaum.

In Figure 4.1, a data center network stack with three hierarchical WAN layers are shown. The first hierarchical layer, the global level, has a wide area network (WAN) connected to two internet service providers (ISP) as its root node. For the purposes of this work, the WAN is an abstraction of a network that connects a set of data center facilities with each other. The second layer of the global level are the metropolitan regions. In this layer, the ISP links are shown as coming in from top and the outgoing links from the bottom serve local distribution networks to buildings within the metropolitan areas. The final layer of the global level are the data center buildings, where the global network links

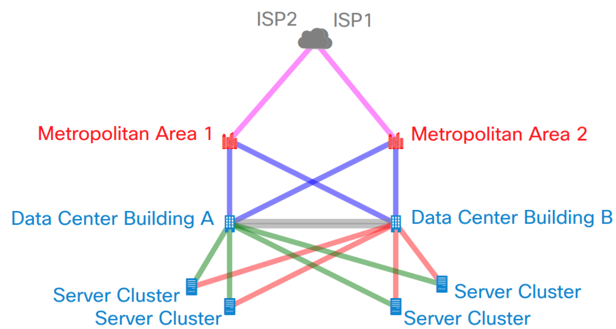


Figure 4.1: General Topology of data center networks. The 1:1 metropolitan area to building relationships are shown for clarity only. Pink: indicates the first layer - ISP-Metropolitan links (physical). Magenta: indicates the second layer Metropolitan-DC Building with a full mesh connection (physical). Gray: represents the cross-connection between Data Centers (logical). Green/Red: Cluster to Cluster links (logical).

connect to clusters of servers. Inside each data center there may be another independent hierarchy as shown by the server clusters. The physical network links shown in Figure 4.1 connect the buildings to each other through the WAN. However, the physical links (pink, magenta) is transparent for the clusters, which directly communicate with each other through logical links (gray, green, red).

Large cloud data center operators have championed WAN systems for global uptime (service availability) and user experience optimizations sushant13 hong13. Cloud data centers are a specific class of data centers. They serve business functions that require custom IT and building systems tuned for optimality in total costs of ownership models. These facilities house numerous services that can be controlled by network load balancers, with each data center limited by its physical infrastructure's capacity. As described by Sushant and Hong, the WAN networks can shift loads between data center on command. The efficacy of a strategy for shifting computational loads depends on the capacity headroom of the physical resources at the data center where the loads are shifted to.

The location fungibility enabled by WANs is desirable from a service application performance point of view, as latency can be significantly reduced for specific markets and applications by minimizing the round trip communication times with consumers. Furthermore for cloud DCs, researchers have demonstrated cross awareness of BEMs and network models to optimize DC sustainability tripathi17, kiani17. Beyond the sustainability gains, there is a potential for meaningful financial incentives by balancing workloads across DC, thus reducing the peak demand on any specific DC and lowering the required physical capacity that must be built.

In the context of BEMs, there is a trade-off with the non-deterministic nature of network load balancing described above. Implementations of load balancing strategies using WAN's make the IT workloads temporally (and geographically) unstable, rendering it elusive for building modelers to reason about. As an example of temporal and geographical instability of data centers, Figure 4.2 barroso18 shows the difference in utilization rates for two server clusters from Barroso's operational experience. This behavior of IT loads is something that WAN aware BEMs can help characterize and exploit. One possible means of exploitation is to flatten the peak of each cluster by routing the excessive workloads to another similarly provisioned cluster with lower coincident demands and sufficient building systems capacity headroom. However, building energy simulation need to be aware of more then just energy to make the right environmental decisions. To effectively optimize environmental objectives, BEMs coupled with MEC models can quantify the energy's global warming potential in terms of carbon footprint to shift loads from one building to another.

Based on the literature reviews and references cited, there are no publicly available simulation frameworks that couple the dynamic data center workloads and the coincident carbon footprint associated with powering their load. The marginal cost of energy coupled building energy model described in this research is the first publicly available tool to allow owners, designers, and researchers to quantify the carbon footprint of data center operations accounting for granular supply and demand matching of power. Next, a literature review of past works concerning the carbon footprint of data-centers and digital services is presented in the Similar Works section.

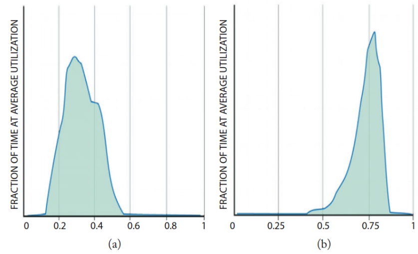


Figure 4.2: Activity distribution of a sample of 2 clusters, each containing over 20,000 servers, over a period of 3 months. The x-axis indicates the server utilization rates (0 to 1) and the y-axis indicates the fraction of time during the 3 months barroso18. The figure on the right (b) shows that peak utilization exceeds 75% with little variances over the 3 months, whereas the right figure (a) shows that utilization is below 60% at all times.

4.5 Similar Works

There are two notable past works that look at the energy footprint for distributed sets of data centers. First, Tripathi considers hardware capital costs alongside with energy acquisition costs to quantify the total costs of ownership in tripathi17. Tripathi,s framework is dynamic in terms of workloads but it is not aware of the building energy dynamics. In the second work, Kiani and Ansari describe a geographical load balancing strategy that exploits green energy mix in the utility grid kiani17. However, their load balancing scheme doesn,t provide insights into how the load balancer evaluates the building energy demands or how the greenness of the energy supply is obtained.

Using a life cycle assessment framework, Whitehead demonstrates a comprehensive data center site level life cycle costs analysis in whitehead15. All energy use in Whitehead's models were deduced from annualized PUE values, precluding coincident energy source evaluations with their framework. Similarly the Green Grid's data center life cycle assessment guideline is limited to PUE as their suggested basis for the operational energy proxy tgg12. The PUE metric is shown in Equation 4.1, it has proven to be the most popular method for data center operational efficiencies since 2006 wiki$_{pue}$.

$$PUE = \frac{E_{total}}{E_{IT}} \tag{4.1}$$

Figure 4.3: Data center locations

$$E_{total} = \text{Total Power Used at Facility}$$

$$E_{IT} = \text{Power Consumed by IT Equipment}$$

Other's have evaluated the costs of internet services koomey08,shehabi14. Taylor and Koomey quantify the energy and greenhouse gas implications of online Advertising circa 2008. While Shehabi evaluates the energy and greenhouse gas implications of video stream circa 2014 shehabi14. Together these works provide a taxonomy that can be followed to assess internet service costs in terms of energy use.

4.6 Methodology

In this section the MEC model,s coupling with the BEM is described. The resulting model maintains a strict partition between the two technical domains. The first part of the model simulates the hourly energy demands of a set of five data centers in EnergyPlus (EP) using the method demonstrated in kumar20. These data centers are distributed across the globe as shown in Figure 4.3. Then in the second part, the data center demands are matched with the respective region,s utility power generation sources for the coincident hour to assess the MEC during that hour. These parts are described in the following subsections.

A fundamental component of the demonstrated implementation of this framework is the network traffic simulator from kumar20. The simulation produces a time-series profile of the network traffic that a hypothetical service will get at a particular data center site. The hypothetical services are based on Wikipedia and segregated according to the natural language of the Wikipedia pages. By segregating services by natural languages allows the treatment of each language as a 'service platform'. With these network simulations, one or more languages can be supported from a single data center with the constraint that the sum of the IT workloads does not exceed the capacity of the data center facility.

4.6.1 Building Energy Model

For the first part, a sufficient building energy demand profile is simulated as in kumar20. The IT workload profile characterizing the power and cooling load is obtained by simulating the 50th quantile of daily network traffic to each data center using Kumar's method from kumar20b. There are three notable differences between Kumar's orginal BEM and the model presented here. The specific changes are:

1. Setting $2kW/m^2$ as the IT equipment load density to represent cloud DCs with hot-aisle/cold aisle containment resulted in run-time errors. This persistently led to thermal runaway conditions for the Singapore and San Francisco sites in the new model. In order to keep the building envelope form-factor and the construction materials the same, this simulation's IT power load density is changed to $1.0kW/m^2$.

2. In these simulations, the data center model has air distribution flow control with approach temperatures specified. Flow control with approach temperature method calculates the temperature differences between the IT hardware boundaries and the air handling equipment. This method is more representative of modern data-center operations and allows modeling ASHRAE 90.4 Standard's requirement of hot-aisle / cold-aisle compartmentalization. The alternate method in EnergyPlus considers the entire data center room as a well-mixed environment, consistent with the modeling

from kumar20. While using the approach temperature method, the cooling set-point is changed to 27 degrees Celsius from 25 degrees used in kumar20. This 2-degree adjustment corresponds with the approach temperature between the air handling equipment discharge and the inlets of the ITE; as there is no mixing of the supply air before it enters the ITE.

3. As the third and final change, the load distribution values in the EnegyPlus input file (IDF) were revised from the SequentialLoad setting to UniformPLR. In the former, equipment is activated in the order listed in the IDF. With this specification each piece of equipment ramps sequentially from its idle state to full capacity, before subsequent equipment is enabled. In the latter load distribution specification, all equipment are loaded in parallel to each other. Another available setting for load distribution, the Optimal specification, was also tried for this field, but it crashed the simulations.

To validate that the proposed building energy model configurations with the above changes produce reasonable results, each data-center is simulated with two models. In the first model, the economizer for the direct evaporative cooler (DEC) limits are increased while in the second model the default settings are maintained. The summary of the changes are indicated in Table 4.1, while the comparison of total site energy between the two models for each set of the simulations is illustrated in Figure 4.4.

In Figure 4.4, the pairs of simulations for a DC site are presented. In the figure, the red bar indicates the total site energy of the model with economizer limits increased and the IT loads reset by the network coefficient (RL). The blue bar indicates the default economizer values (NoRL) from Kumar and with statically configured IT load profiles (ie cyclic day/time load). From the figure it can be observed that the increased economizer settings lead to more energy use than the default values for three of the five DCs. This increase in energy demand is attributed to the load resetting, where the network aware model increased the IT load for more hours of the year.

Table 4.1: Economizer settings for the two models

IDF Object	Variable	Default	Increased
DC-OA	Econ. Max db-C	23	28
DC DEC	Evap. Max db-C	20	28

Figure 4.4: Total Site annual energy for statically (NoRL) configured IT load and dynamically reset (RL) IT loads.

The next subsection introduces the marginal costs of energy model, which will take the results from the BEM model described above.

4.6.2 Regional Marginal Costs of Energy

The second module requires a time-series profile of the electrical grid's power source attributions, where the intervals of the power generation values match the BEM energy profile. The corresponding site and regional grid model pairs are indicated in Table 4.2. For this model the energy generation regional grid profiles are obtained from Platt, who provides profiles for 13 US regions in DOSCOE [5]. Singapore and Amsterdam data-centers grid profiles are constructed as described below.

Each U.S region's grid profile is composed of hourly demands and corresponding production capacity of several power generation technologies. Hourly values for each region's demand, solar, wind, coal, coal with cryogenic capture, coal amine gas scrubbing, and nuclear are defined. These grid regions are representative of three out of five of the

Table 4.2: Data Center Site and Power Grid

DC ID	DC Location	Regional Grid
SFO	San Francisco, CA	California
CAR	Carrolton, Texas	ERCOT
ASH	Ashburn, VA	Midatlantic
AMS	Amsterdam	Netherlands
SIN	Singapore	Singapore

data-center locations being simulated.

For Singapore, the International Energy Agency (IEA) provides a top down view of the annual energy production from various technologies. The IEA data shows that the renewable penetration in the energy supply for Singapore accounted for only 1.6% of the total energy demand in 2016 IEA17. Due to this negligible contribution from renewable sources and lack of hourly generation data, it is assumed that all demand is met by natural gas power generators, consistent with other sources eia20. Figure 4.5 indicates the energy production capacity and the associated carbon emissions for each of the utility grid regions. The demand profile for Singapore in 2016 is obtained from sin16.

For the Amsterdam data center, the energy profile of Netherlands is used. The IEA indicates that in 2018, 12% of Netherlands' energy demands was met by renewable sources. This is a meaningful contribution from renewable, therefore a more granular generation profile is prudent as opposed to Singapore which did not require evaluations of the energy mix at any given time. To formulate a more granular resolution of the Netherlands' generation, the IEA data is supplemented with data from the Open-Power-System-Data to characterize the time series profile of renewable energy ospd19. OPSD provides hourly data for the renewable sources only. The balance of the energy demands in the Netherlands is met by fossil fuel-based generators, namely 35% by coal and 42% by natural gas eia20b. The DOSCOE grid profiles don't have any corresponding field for bio-mass, so the bio-mass generation indicated in OPSD is lumped in with the fossil fuel generators. In the discussion section, some validation for this approach is presented. The Netherlands also produces nuclear energy, but only the annual production rates were obtained eia20b. In this works implementation of the DOSCOE, the annual nuclear production for Netherlands is distributed equally over the year and modeled as a constant (non-dispatchable) base load throughout the year.

The MEC coupled BEM algorithm is given below. In the algorithm two inputs are required. The first is DOSCOE[region], it is a two-dimensional array formatted as described in platt17. It indicates hourly grid profiles of the power demand and power capacity of the available energy sources at the corresponding hour. The second input, traffic.language, is a one-dimensional vector indicating the network traffic to the respective site from [48]. In the algorithm, for each language, it's traffic to the respective data center is checked. If there are traces of a language routed to a site, the algorithm performs the BEM simulation by invoking EnergyPlus. This resulting demands from EnergyPlus are then added to the region's grid demand profile. If a language does not have any traffic to a particular site than, the data center site does not do any work and the BEM simulation is bypassed.

Algorithm 3 MEC coupled BEM algorithm

Require: DOSCOE[region] & traffic.language[site]
  for site and region in DC.site and DC.region **do**
    if traffic.language[site].all $!=0$: **then**
      $DEMAND_{DC} \leftarrow BEM(site, traffic.language)$
      $DOSCOE[region].demanddemand[site]$
    end if
  end for
  CO_2 footprint $=$ $GridSim(region, rps)$

  Where $DEMAND_{DC}$ is the marginal demand the data center puts on the power grid,

The second step of algorithm quantifies the marginal carbon footprint of the grid with the added data center loads by running DOSCOE's Grid Simulator. In this step, the renewable portfolio standard (rps) argument specifies the percentage of renewable energy mix for the region.

In the next section the results from the methodology are discussed.

4.7 Results & Discussions

The resulting values of the carbon footprint for each data center is summarized in Table 4.3. The energy model for the 491 kW data center has been scaled by 1000 to represent the metro scale of data centers impact of the regional grid. The specific data center model represents only a small fraction of hyper-scale data centers campuses that reach 500-Mega-Watts. The table further indicates the carbon footprint of each of the languages being served from the data centers. The values are indicative of the marginal CO_2 emitted by adding the data center demand to the respective grid.

Site	German	English	Spanish	French	Japanese	Russian	Chinese	Total
California	0.0	1.24x10^6	0.0	0.0	0.0	0.0	0.0	1.24x10^6
Carollton	0.0	6.59x10^4	1.20x10^6	0.0	0.0	0.0	0.0	1.26x10^6
Ashburn	0.0	4.38x10^6	8.0x10^5	1.17x10^5	0.0	0.0	0.0	1.36x10^6
Amsterdam	2.81x10^5	2.25x10^5	9.85x10^4	2.67x10^5	0.0	3.15x10^5	4.67x10^4	1.23x10^6
Singapore	0.0	3.74x10^5	0.0	3.71x10^4	3.35x10^5	3.91x10^5	7.87x10^4	1.22x10^6
Total	2.81x10^5	2.35x10^6	2.09x10^6	4.21x10^5	3.34x10^5	7.06x10^5	1.25x5	6.31x10^6

Table 4.3: Data Center Operation Carbon Footprint (Tonnes of CO2 Emitted over the Year)

Table 4.3 indicates the total marginal carbon footprint for each language in the last row by summing each of the language columns. While the total marginal carbon footprint of each data center is obtained by summing the rows as shown in the last column. The English pages have the most traffic globally and as expected English has the largest marginal carbon footprint due to its data-center operations. Form the physical data center perspective, the model shows that the Ashburn data center has the highest carbon footprint. This can be attributed in part to the energy source's carbon footprint relative to other locations as shown in Figure 4.5.

Figure 4.6 is a histogram plot of the PUEs for all the data centers in the evaluated network. Each color in the figure represents a specific data center. The PUE is indicative of the utilities system efficiencies; namely the cooling and the power distribution The x-axis in Figure 4.6 indicates the PUE value and the y-axis indicates the number of hours the data centers have at specific values. As a concrete example, the bars representing Netherlands site is labeled as ams-rl_PUE and has most hours at or below a PUE of 1.1. Other data centers also have a PUE of 1.1. Stacking the curves from the different data centers indicates the global network's time spent at a specific PUE. A major influencing factor for the PUE is the local weather conditions.

An understanding of the cooling design weather conditions may help reason about the differences in PUE. Lower PUEs generally coincide with cooler weather, which leads to more favorable thermo-mechanical equipment operating points. In practical terms, cooler temperatures enable facilities to be cooled with economizers for more hours and they also lower the equipment's energy demand when economizers are not fully operational. For the set of the data center analyzed in this work, the ASHRAE cooling design conditions are shown in Table 4.4 (from [49]).

DC	$0.4\%DB$	$0.4\%WB$	$1\%DB$	$1\%WB$	$2\%DB$	$2\%WB$
Amsterdam	82	67.5	78.1	66.2	74.6	64.4
Ashburn	93.5	75.1	90.8	74.3	88.2	73
Singapore	91.7	79.4	91.1	79.4	89.9	87.2
Carrolton	100.4	74.5	98.4	74.6	96.2	74.8
San Francisco	83	63	78.3	62.1	74.4	61.2

Table 4.4: ASHRAE Annual Cooling and De-humidification Design Conditions in $^\circ F$ [49]

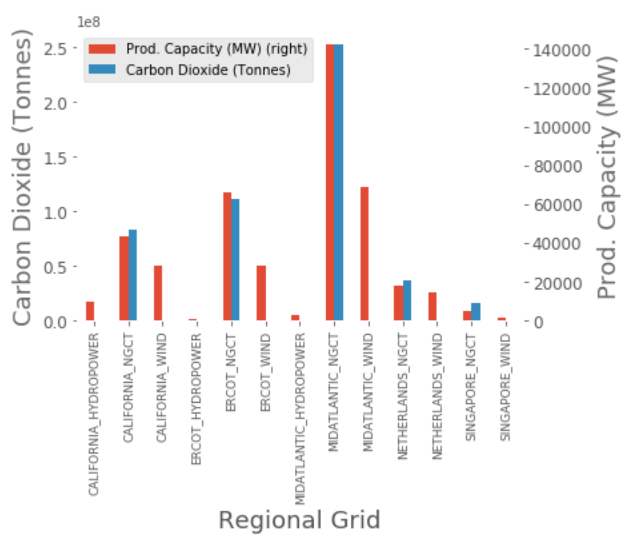


Figure 4.5: Energy Product Capacity and Carbon Emissions.

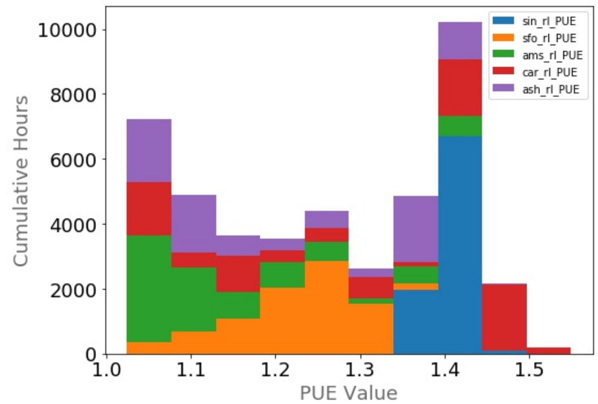


Figure 4.6: Stacked histogram of PUE from all Data Centers.

As an implementation detail, the DOSCOE model proved to be quite sensitive to the data structure of the load profiles. For example any null value in the profile resulted in breaking the linear solver. Also, solar and wind energy are required to be non-zero for at least one hour of the year. This requirement is a practical constraint, but in the profile developed for this work the values are arbitrarily set to a low value across all hours. Specifically, the defaults setting used in the work is 0.1 MW for each hour.

Another implementation measure required the discounting of facility's base loads. Without this discount, each model accounted not only the incremental load placed on the DC from a service's incoming traffic, but also it would account for the entire baseline loads in each EnergyPlus run. For sites with multiple services, this results in significantly over accounting of the base loads, as it would be included for all the services in the DC. To address this issue, a post processing step apportioned the baseline load to each service/language by using the traffic coefficients. For the attributions, an initial condition for the traffic coefficient is set to 0. With this initial condition, the BEM provides the baseline energy required by the data center (i.e. all equipment operating at their lowest turn-down rates). The traffic coefficient scaled this value, bound by the constraint that the sum of the coefficients is strictly equal to 1 for all time-steps of the simulation.

4.8 Conclusion

The network dependencies between physically dispersed data center resources make system level building design decisions a challenge to reason about. This research has presented a quantitative method to couple the network dependencies of data centers with their building energy and grid level marginal costs of energy. The research extended the PUE metric with utility grids to indicate carbon footprint of data centers. Furthermore, as shown in Table 4.4 the presented method allows analysis of data center systems at global service levels.

As pointed out in the background section, there is a lack of bottoms up building design and carbon footprint models. The modular methodology of this research is a novel means of coupling abstracted service level metrics (WAN traffic in this case) with physics based building energy simulation (EnergyPlus in this case). This integrated tool set can be used by data center system modelers to optimize their deployment across geographical bounds. Future work should consider controlling the network traffic based on building energy simulations to achieve global optimality in real time operational environments.

Chapter 5

Life-Cycle Energy and Carbon Footprint Modeling with Data Center Building Energy Models

5.1 Introduction

In this chapter, the aim is to quantify the end to end life cycle costs of data centers by extending the operational models developed in the previous chapters. Those operational models have provided an indication of system level energy for a network of data centers and their marginal carbon dioxide footprints. Although, the presented models are a good proxy for the environmental costs of data center operations, they don't account for the energy and carbon footprint embodied in all the materials that the data centers are composed of.

To assess the end to end environmental impact of data centers, this chapter describes a three-step hybrid life-cycle analysis inclusive of operations and embodied inventories of the physical data center infrastructure. First, a review of two previously developed models for building energy and marginal costs of energy generation is provided. These models together provide an indication of the energy and carbon footprint during the operational phase of a data center's life. Second, a life cycle modeling framework using an economic input-output (EIO) analysis model extended to environmental costs is introduced. The inputs to the EIO are compiled in this chapter based on literature reviews and the researcher's industrial experience. The third and final step provides a global scale end-to-end assessment for the energy and carbon footprint of each data center language pair analyzed in the previous chapters by adding the operational and embodied components associated with them across the DC system. With the system level view, the global environmental costs of discrete language (service) can be assessed.

5.1.1 Motivations for an end to end life cycle cost model

In terms of scale, US data centers consumed 700 billion kWh in 2016. That was 1.8% of the total electricity produced in the country according to a United States Department of Energy (DOE) report [30]. To drive further intuition of their scale, a typical 100-MW data center at peak load consumes the same amount of energy in an hour as 100 homes do in a month. Given a data center's power demands, it is not surprising that operational energy use has a high sensitivity towards their total cost of ownership (TCO), making it a key metric in TCO based design decisions. While optimization for use phase energy may significantly reduce the carbon footprint of a data center (given the source energy mix does not change), it does not account for other phases in the data center's end to end life cycle. Inventories from embodied life cycle phases such materialization, transit, maintenance, and end of life are left out of the operational phase energy models that have become prevalent indicator of data center sustainability.

There are two predominant paradigms for evaluating the embodied environmental inventories for any product that has been altered by technology (techno-sphere). The first method is process based. The complexity of a process-based model is greatly influenced by the boundary conditions of the study. If the boundary is demarcated between the biosphere and the techno-sphere, then the number of distinct life cycle processes to quantify explodes by 500 times for a simple pen [1]. The alternate method is based on Leontief's macro-economic proxies that exploit economic correlations between industrial sectors. In macro-economic models, a matrix with rows and columns equal to the number of sectors in the economy is populated with the cost relationship between the row-sector and the corresponding column-sector. Industrial-sector macroeconomic proxies reduce the problem space significantly as only one cost vector is required as input to analyze an entire economy. This research combines the two paradigms and presents a hybrid life-cycle assessment model of data centers that can be used to support data center design decisions.

The structure of the paper is as follows. First, some technical background about data centers is provided along with a synthesis of similar works. Then in the methodology section a dynamic model to quantify the operational and embodied costs of data center infrastructure is described. The results from the methods are then presented in the results section. This article concludes by summarizing it's findings and suggesting the future direction in this area of research.

5.2 Background

5.2.1 Technical Overview of Data Centers

Modern internet data centers are district scale systems, spanning campuses that are hundreds of acres. They may contain several hundred thousand pieces of information technology (IT) equipment. IT equipment consists of physical servers, network hardware nodes, and digital storage media. Theses pieces of IT equipment sit alongside the data center's district scale cooling and electrical distribution plants housed in warehouse-scale built environments. The environmental footprint of a data center spans the full breadth of these physical pieces of infrastructure.

At their scale data centers receive power through medium voltage connections with the local utility's grid. The alternating-current voltage may then be stepped down in several steps, but ultimately, it is rectified to be used by the sensitive electronic components in the information technology hardware. Each step-down is a point of power inefficiency, with the alternating-current to direct-current conversion being the biggest point of power loss. Furthermore, wherever the step down or conversion occurs inside the building, the electrical inefficiencies are manifested as heat.

The heat from the electrical inefficiencies, along with the heat emitted by the IT equipment transistor state transitions and their current leakage, must be rejected to the outside of the building space by mechanical means. At a fundamental level, a mechanically driven fluid mover is needed to convey the heat from indoors to outdoors or another reservoir. In single pass cooling systems fans intake outside-air and force them through the IT equipment, capturing any heat and carrying it outside of the buildings. More complex cooling systems may include liquid or gas refrigerant medium thermodynamic cycles between the buildings and reservoirs, with the refrigerant medium capturing heat at either the building room level or at the scale of IT equipment. Precise modeling of such data center building systems with intense therm-power dynamics is now a manageable task in building energy modeling software [47, 48].

The embodied costs of IT equipment and building systems yield additional environmental costs for a data center's life cycle. The rate of innovation for IT equipment and the ever-increasing demands from the software applications creates a capital market where TCO of one generation of IT hardware rapidly increases relative to newer IT hardware solutions. The capital of cost/performance trade-off makes the positive TCO life of IT equipment between two to five years as observed by Shehabi in their DOE report [30]. This relatively short lifetime of IT further compounds the embodied costs of data centers. For example, through a 20-year data center building life, four to ten generations of IT transit through the facility. Disparities in lifetimes and dimensional scale differences between buildings and microchips make data center embodied inventory modeling complex. However, recently hybrid life cycle assessment models have shown to be effective in quantifying the embodied costs of data centers [1, 5].

Information technology equipment requires some further insights in order to make its impact to data center life cycle analysis more concrete and directed in scope. At the heart of information technology equipment are microprocessor chips. Modern chips are composed of billions of transistors which have been getting smaller in size since their first applications in electronics signal processing in the 1960's (see Figure 1.2). Transistors have been the key enabler for the compaction and power efficiency gains of electronic devices over the years and they've also been shown to have one of the most dominant environmental costs within electronic products [50, 51].

Prior to the mid-2010's, transistors were composed of planar or 2-D architectures. 2-D transistors inherently had limited operational power efficiencies due to higher voltage and current leakage compared to the novel 3-D processors in the market today. Specifically it's the 3-D processes that have allowed significant operational efficiency gains for data center operators, yet studies assessing the 3-D transistor architecture's impact to data center life cycle costs are lacking, exception being [52]. The 2-D to 3-D transition is a recent example of rapid rate of adaption for information technology equipment that make generalized environmental impacts studies for transducer technology obsolete in two to three years [53]. The frequent churn of technology also drives rapid changes in the manufacturing process of the chips. These rapid changes in semiconductor-manufacturing processes necessitates a parametrically scalable framework where transistor chips can be evaluated in isolation from other server components.

5.2.2 Similar Works

In this section similar works that have quantified the environmental footprint of data centers are presented. Data center life cycle assessment works come from industrial operators [1], academia [5, 52], federal agencies [6], and industrial consortium [16]. Two of the reviewed works are conducive to replicate from the ground up [1, 5], while another serves as a guideline [16], and another provides an online interactive tool to assess the footprint of targeted classes of Cloud services [6].

From an operators perspective, Shah demonstrates an end to end life cycle assessment of data center systems [1]. Shah uses a hybrid model inclusive of process based and economic input-output assessment frameworks to assess a single data center, while using a static model for use-phase power. Whitehead extends Shah's hybrid work and demonstrates the life-cycle costs of a real data center and sets an explicit functional unit of 1-kW of provisioned capacity [5].

The recent focus on operational energy efficiency for consumer products motivated Kline's study of the trade-offs between operational energy and the embodied costs of information technology equipment [52]. Although their derivation of the embodied costs are process based, their literature does not provide sufficient insight for others to reproduce the work. Similarly, the Green Grid's data center life cycle costs guidelines outline the end goal of a data center life cycle analysis. It classifies several key attributes that need to be considered, but lacks references to explicit procedures that must be followed to achieve the goals.

The Cloud Energy and Emissions Research (CLEER) Model provides a browser based user interface to compare the environmental costs of on-premise server based services with hypothetical cloud-based systems that would provide an equivalent service [6]. CLEER's analysis is transparent and inclusive of embodied and operational costs, but it does not dynamically couple embodied or operational costs into the model. The presented set of past works inspired the methodology of this research as described in the next section.

5.3 Methodology

5.3.1 Functional Unit and Reference Flows

Life cycle assessment studies require a functional unit of performance of the system under study for use as a normalized reference point. As a reference point for data centers, there is an industry wide consensus that power is the best indicator for a data center's workload capacity [1, 5, 2]. Based on the consensus, the functional unit adapted for this research is chosen to be 1-kW of provisioned power per year as used by Whitehead.

Furthermore, for the abstracted functional unit to be used in comparisons between different data center design scenarios requires it to be translated to reference flow values. In this work the reference flow is constrained to 1-year of data center operations with the globally provisioned power footprint of each of the language abstracted internet services. The language (internet service) to data center distribution is indicated in Figure 5.1.

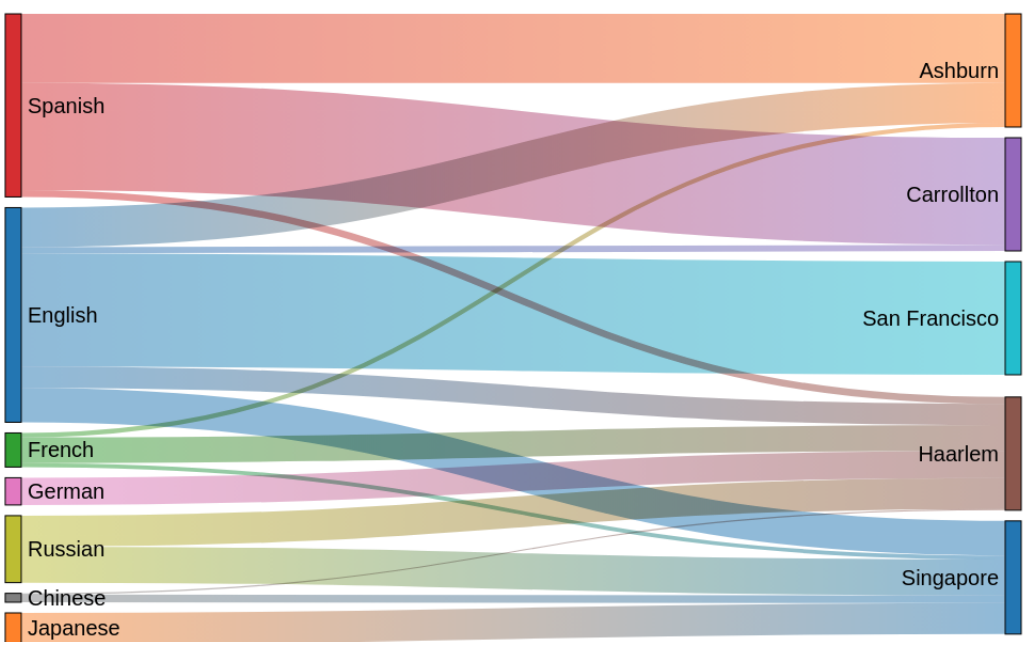


Figure 5.1: Language to data center flows. The thickness of the links at each data center site indicate the relative portion of traffic that the respective language demands at the data center.

5.3.2 System Boundary

The presented framework is intended to be used as a tool in data center life cycle assessments (LCA), where prevalent LCA practices are followed. In standard practice, product specific LCA studies generally entail four phases: 1) goal and scope phase, 2) the inventory analysis phase, 3) the impact assessment phase, and 4) the interpretation phase [18]. The methodology, data sets, and software tools presented in the research is conducive for the first three LCA phases which all require quantitative assessment of data center environmental footprints. Stated more explicitly, this research's goal is to provide a model that can be used to quantify the energy and carbon footprint of data center systems encompassing the embodied and operational phases in a single workflow.

Figure 5.2 illustrates the boundary conditions of this framework. Within the boundary and inclusive to the scope of the presented model are the raw materials and energy from the ecosphere. From the raw materials two paths lead to the embodied systems found in data centers; building construction and information technology manufacturing. While the other two path lead to the operational systems that are required to run the data centers.

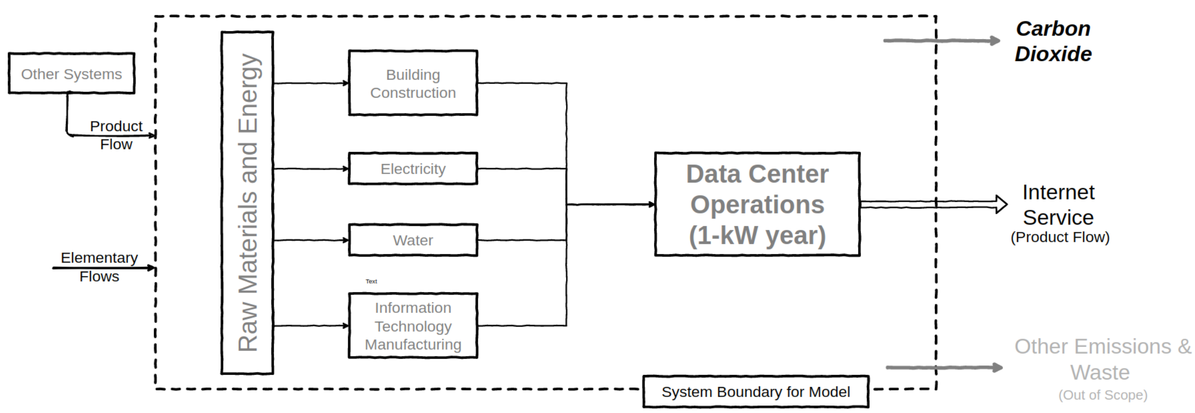


Figure 5.2: System Boundary for 1-kW of Provisioned Data Center Capacity.

The geographical bounds of the service are illustrated in Figure 5.3. The map indicates the countries in which each language from the Wikipedia set are the official natural languages. From Figure 5.1 it can be seen that one or more languages is supported at a single data center facility. Although the workloads originate across international boundaries, the environmental emissions studied in this research are attributed to the data center sites only.

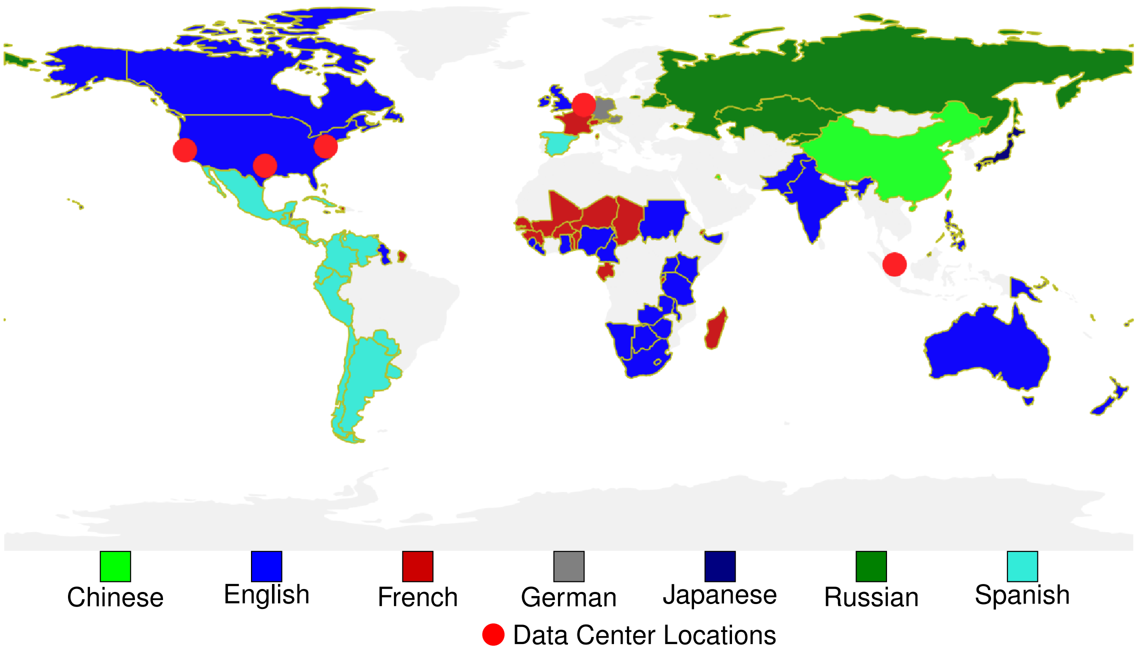


Figure 5.3: Source country of language and DC locations map.

Within these data center sites, specific sub-systems are segregated as listed in Table 5.1. Demarcation by these sub-systems allows development of the embodied and operational models to align with industrial cost breakdown data and in terms of EIO industrial vectors. Table 5.1 serves the structural backbone for all the models developed in this framework as discussed next.

System Boundary	**Examples**
Building Systems	Data Center Shell and Core
Cooling Systems	Air Handling Units and hydronic plants
Power Distribution	UPS, PDU, Cables, Diesel Generators
Information Technology	Compute, Storage, Network

Table 5.1: Sub System Boundaries

5.3.3 Operational Inventories

In this section, this research's methodology to assess the operational energy and carbon footprint of data center site infrastructure is presented. There are extensive theoretical data center energy use models in the literature [54, 13]. These models can generally be segregated between IT and building systems domains. The model developed in this research couples the two domains by first selecting the appropriate IT component to model, i.e., the IT component that the total energy of the data centers is most sensitive to.

Detailed industrial power usage insights are lacking in the public domain [55]. As an exception some industrial insights are provided by Barroso in [2, 22]. Barroso provides Google's distribution of power for various points-of-use as indicted by the pie-charts shown in Figure 5.4 for two generations of technology. In 2012, more than 80% of the energy in a data center was used by four components; CPU 42%, Cooling 15.4%, disk 14.3% and DRAM 11.7%. By 2017, the cooling overhead had decreased to only account for 3% data center energy use, this decrease in cooling inflated the relative fractions of CPU and DRAM energy requirements. From these distributions, it is apparent that CPU's power usage is the dominant hot-spot.

The values in Figure 5.4 are annualized distributions. In practice the power demand of data centers is very dynamic and sensitive to complex workload dependencies. These dependencies lend themselves to be exploited in power proportional computing paradigms. Several proportional workload techniques are discussed in detail by O'Sullivan in [56]. This research takes such techniques and extends building energy models to be aware of proportional CPU loads based on coming network traffic to a data center site in an EnergyPlus model.

EnergyPlus provides a comprehensive indication of the operational energy and together with the marginal cost of energy model from Chapter 4, the proposed framework exposes the carbon footprint for each of the five data centers and the language abstracted

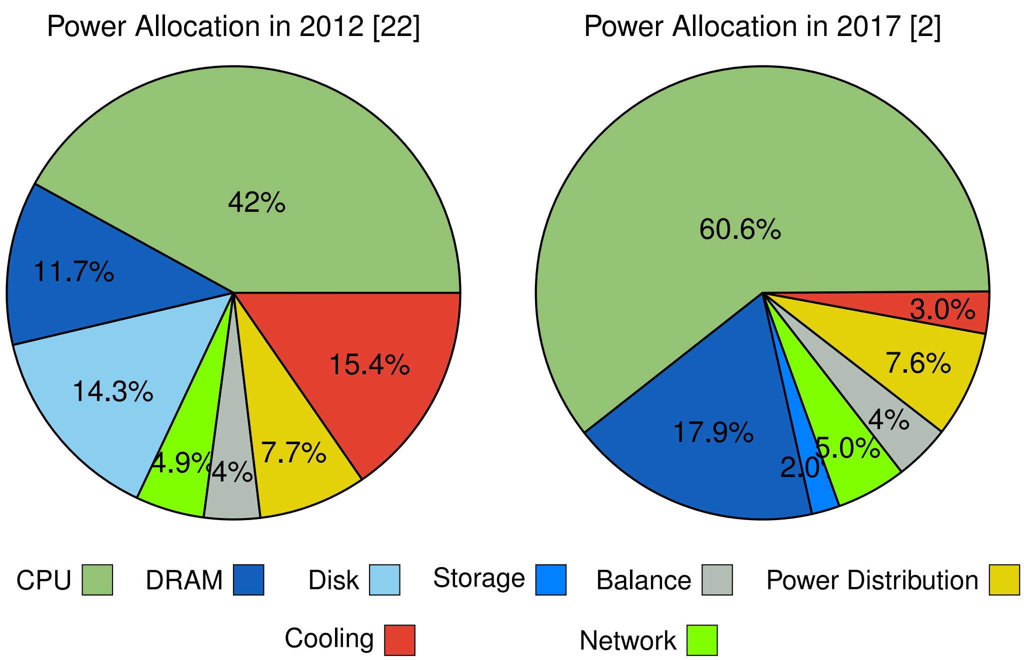


Figure 5.4: Data Center Power Distribution for Two Generation of Technology

service pairs. The network coefficients from Chapter 2 are used to reset the IT workloads at each time-step in EnergyPlus. The resulting energy demand at the time-step (hourly) is then passed to the MEC model from Chapter 4 to evaluate the marginal carbon footprint for that hour in the respective utility grid. The details of the model are indicated in Algorithm 4 and the general framework is illustrated in Figure 5.5.

The configuration of the model is as presented by Kumar in [48]; where the provisioned IT capacity of each data center is 492-MW. This provisioned capacity is scaled from the EnergyPlus simulation of the 492 kW DC to represent metropolitan sized data center nodes that reach 100s of MWs. The scaling allows the research results to be more pronounced at the grid level, sufficing for the demonstrative objective of the prototype model. The specific data center wise allocation of each language is indicated in Figure 5.2.

Algorithm 4 MEC coupled BEM algorithm

Require: $DOSCOE[region_i]$ & $traffic.language[site_{DC}]$
  for site and region in $DC.site$ and $DC.region$ **do**
    if traffic.language[site].all $!= 0$: **then**
      $D_{DC} \leftarrow BEM(site, traffic.language[site_{DC}])$
      $DOSCOE[region].demand += D_{DC}$
    end if
  end for
  return CO_2 footprint $=$ $GridSim(region, rps)$

Where:
$DOSCOE[region_i]$ = Dispatch Optimized System Cost of Energy Model for $region_i$ [57].
$site_{DC}$ = data center site.
$traffic.language_l[site_{DC}]$ = the traffic routed to data center for lanuage l.
$DC.site$ = list of all data centers in the network.
$DC.region$ = list of corresponding power grid region for the data centers in $DC.site$.
$DOSCOE[region].demand$ = demand vector of loads added to the power grid for every hour.

External Models:

$BEM(site, traffic.language[site_{DC}])$ is a EnergyPlus model of the data center. As an external argument the traffic profile for the language to the data center is passed. The traffic profiles serve as coefficients for the IT load, bounded by 0 and 1. The output is a vector indicating the building energy demands for each hour of the year.

$GridSim(region, rps)$ is a DOSCOE model with $DOSCOE[region].demand$ and renewable portfolio standard (rps) value indicating the required penetration percentage of renewable energy in the power supply. The model quantifies the costs of energy in terms of carbon footprint and monetary values.

5.3.4 Embodied Inventories

Embodied cost assessments account for the natural resources consumed when extracting, transforming, manufacturing, transporting, constructing, maintaining, and disposing the product under study. The first step in these assessments is to set the boundary conditions of the system. The second step is to select the method of the assessment. Two methods are available for such assessment; namely process based or EIO based. Process based methods are bottoms up procedures; accounting for all processes that are required to transform raw materials into consumer goods. However, in process based methods as the product boundary expands linearly to account for more components, the processes to quantify can expand exponentially. This exponential growth can become an intractable task for building designers. A more tractable method is the EIO, where

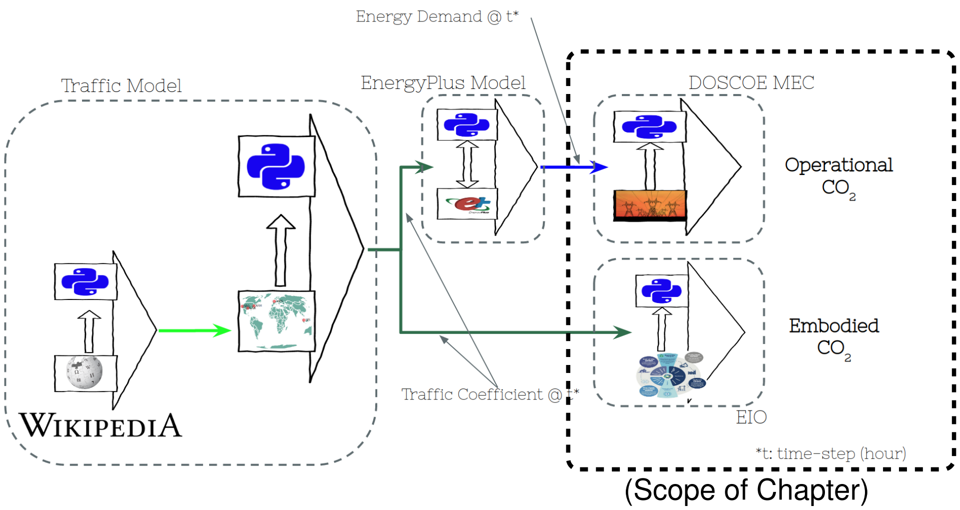


Figure 5.5: Model Process Flow Diagram.

Language	Site	Allocation %	Allocation MW
English	Ashburn	35	172
French	Ashburn	4	19
Spanish	Ashburn	61	301
English	Carrollton	5	27
Spanish	Carrollton	95	465
English	Haarlem	19	92
German	Haarlem	24	118
French	Haarlem	23	112
Chinese	Haarlem	1	5
Russian	Haarlem	27	134
Spanish	Haarlem	6	30
English	San Francisco	100	492
English	Singapore	30	150
Japanese	Singapore	27	135
French	Singapore	4	17
Chinese	Singapore	7	33
Russian	Singapore	32	157

Table 5.2: Provisioned Allocation of Language at each Data Center

economic relationships between two industries at the national level are exploited.

Leontief's original use case of the EIO was to identify the contribution from all economic sectors required to produce a unit of specific products in an economy. The formulation of Leontief's EIO is indicated by Equation 5.1; where Y is the input costs, I is the identity matrix, and A is the direct costs array [58]. In general, direct costs represent the entire economy as a two-dimensional square array, where the rows and columns indicate distinct sectors within the economy. The values in the array indicate the row-index-sector's input into the column-header-sector. In other words, the column-header-sector supplies goods to the row-index-sector as indicated by the value of their intersection position in the array. Since EIO's development in the 1930's, they have been commonly used to characterize national economic accounts. More recently, Matthews and Hendrickson showed that EIO can be used for environmental life cycle assessments as well [58].

$$[I - A]^{-1}Y \tag{5.1}$$

Due to the streamlined approach of the EIO method compared to process based environmental assessments methods, the former is preferred for this research. Specifically, the United States Environmentally Extended Input-Out (USEEIO) model developed by Yang for the EPA is used in this research [21]. The USEEIO's economic relationship between sectors is based on 2007 cost data, while the environmental data are derived from 2013 emissions data. Both were the most up-to-date data available to the researchers at their time of publication. They suggest using 2013 cost of money for inputs, having demonstrated that the underlying structure of the economy has not shifted significantly between 2007 and 2013.

Building Systems

Typically, data center shells and structural cores are under the jurisdiction of the same building codes as other commercial buildings, i.e. Type IIA construction types. However, the dense population of computers along with the power and cooling requirements of data centers make several things clearly distinguishable from most commercial building types. The differences are significant enough to make the generic building sector's USEEIO environmental inventories invalid for data centers.

To more accurately represent data center buildings, several general contractor proposals for new data center construction and retrofit projects were reviewed for the cost distribution of the trades' labor and equipment costs. The contractor cost allocations per trade divisions were then compared with the values of the handful of building construction sectors available in the USEEIO. Based on the comparisons, the USEEIO manufacturing buildings sector is found to be the most similar for data centers. However, there are still shortfalls between data centers and the manufacturing buildings sector. To overcome the shortfalls, a hybrid method was used to construct a more representative Y vector for data centers.

The resulting Y vector to scale the building and building utilities systems is shown in Table 5.3. The table indicates the cost input required to provision a functional unit of 1 kW of data center capacity. Each sector's cost is derived from the contractor costs for the corresponding construction specification division as listed in their proposals. Seven explicit sectors are quantified in addition to the manufacturing building sector. The manufacturing building/us is a catch all sector. This sector catches all the building trades that are not represented by the other entries in the Y vector; such as concrete or steel.

ID	Sector Name	$/kW
333415	air conditioning, refrigeration, and heating equipment/us	550
333611	turbines and turbine generator sets/us	770
335311	specialty transformers/us	50
335313	switchgear and switchboards/us	100
335920	communication and energy wire and cable/us	100
335999	other miscellaneous electrical equipment and components/us	40
335314	relay and industrial controls/us	150
233230	manufacturing buildings/us	5250

Table 5.3: EEIO Costs Vector for Building and Utilities Infrastructure

Information Technology Systems

In this subsection the IT equipment's inventories are assessed. The IT equipment in a data center can be categorized broadly into three segments: compute, storage, and network. Within each of these segments, data center operators can further tune the hardware configurations to optimize their workloads. Figure 5.6 indicates component wise cost distribution for five hardware stock-keeping units (SKU). The SKU data were obtained under non-disclosure agreements from a large internet website operator.

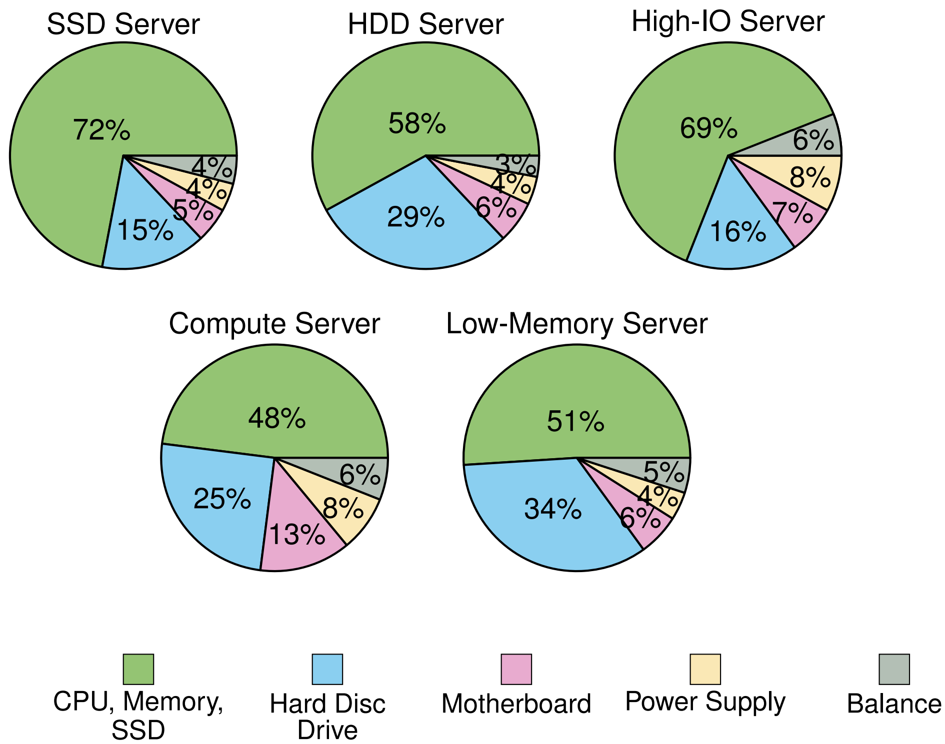


Figure 5.6: Cost apportionment of deployable hardware. See Table 5.5 for details of USEEIO sector mapping. The values are representative of deployment cost share per server during 2015 and 2016. Data acquired by author from an DC operator under NDA.

The configuration of the server SKUs are optimized for the workloads that they support. For example the High-IO server is optimized for high rates of input and outputs; where it processes information at high feed rates. As an example, this is useful for workloads that require external communications with a large data set housed in a storage array (see Figure 1.14 as example) server that has an abundance of data storage capacity. A data center with dominant heterogeneous workloads will have a mix of of these SKUs, whereas a data center with a single workload would have only one or two distinct SKUs.

Server components such as processors (CPU), memory (MEM), and solid-state-drives

(SSD) are fabricated using semiconductor manufacturing processes. These components are grouped together and are categorized as a single input into the USEEIO's semiconductor sector. Hard disc drives (HDD), motherboard (MBD), and power supply units (PSU) have representative sectors that allow a one to one mapping within the USEEIO. Other components such as chassis, thermal-heat sinks, and cable connectors are grouped into the balance category. The balance category is mapped to the generic computer sector in USEEIO. This costs apportionment values can be used to construct the Y vector for input in the USEEIO. At the DC level, the quantities of the components must be scaled up by the count of servers provisioned in it.

Algorithm 5 is used to quantify the count of servers in each data center. Table 5.4 indicates the algorithm's power density value for each component found in each server. For each server the total power is calculated by summing the power for all components in it. The component apportionment for each server SKU is indicated in Table 5.5. For the Y-vector, the failure rates are included in pre-processing step that scales up the apportioning factors from Table 5.4 to account for the failure rate of these devices.

Algorithm 5 IT equipment Y vector algorithm

Require: P_{DC}, P_i, and C_i

$P_S \leftarrow \sum_{i=1}^{n} P_i$

$C_{ip} \leftarrow C_i \times f_i$

$S_{\#} \leftarrow \frac{P_{DC}}{P_S}$

$SC_{DC} \leftarrow S_{\#} \times P_S$

return $Y \leftarrow SC_{DC} \times C_{ip}$

Where:

P_{DC} = Provisioned Power of Data Center, (input variable)
P_i = Power demand for component i of server.
n = Number of components in the server.
C_{ip} = Provisioning cost of component i
C_i = Cost Apportions for server component i. See Figure 5.6.
f_i = Failure rate of component i. See Table 5.6.
$S_{\#}$ = Count of servers in data center
SC_{DC} = Total Server Costs for DC
Y = Vector of sector wise costs for input to USEEIO

Component	Power (Watts)	Reference
3.5" HDD	3.87	[59]
2.5" HDD	0.89	[59]
SSD	0.37	[59]
Single Socket CPU	105	[60]
Dual Socket CPU	210	[60]
Power Supply Unit	25	[13]
Motherboards	40	[61]
RAM	0.375	[62]
Fans (5 per server)	10	[61]

Table 5.4: Server component power distribution

Component	USEEIO Sector	SSD	Mix-HDD	High-IO	Compute	Low-Mem
CPU, Memory, SSD	semiconductors/us	72%	58%	69%	48%	51%
HDD	computer storage device readers/us	15%	29%	16%	25%	34%
Motherboard	printed circuit and electronic assembly/us	5%	6%	7%	13%	6%
Power Supply Unit	Electronic Capacitors and other components (except semiconductors and printed circuit assemblies)/us	4%	4%	4%	8%	4%
Balance of Parts	computers/us	3%	3%	3%	6%	4%

Table 5.5: Cost apportionment of deployable hardware stock keeping units (SKU)

Using the above characteristics of the data center systems, the embodied costs of the systems are amortized over their useful lives. Namely, the building systems are amortized over *20 years*, while the IT equipment is amortized over *3 years*. For both of these systems the annual amortized costs are distributed on a hourly basis over the year. The hourly values are aggregated in a post processing step to indicate the costs relative to the functional unit of 1-kW/year of provisioned capacity. The hourly distribution allows for the network traffic coefficients of each language and data center pair to apportion the total embodied costs for the hour to the respective language and DC pair.

As a final and important note about how the carbon footprint is translated from the USEEIO to a meaningful measure of sustainability. The USEEIO provides environmental impacts associated with the embodied costs of data center components based on the US Environmental Protection Agency's (EPA) Tool for Reduction and Assessment of Chemical and Other Environmental Impacts (TRACI) [63]. The impacts of the carbon footprint

Component	Failure Rate (%)
CPU	0.03
MEM	0.27
HDD	0.67
SSD	2.56
MBD	1.57
PSU	0.30
BAL	0.25

Table 5.6: Annualized Information Technology Device Failure Rates [2, 3, 4].

manifests itself as the global warming potential of the system. Therefore, the carbon footprint indicator from USEEIO is in terms of equivalent carbon dioxide mass.

5.4 Results

In this section the results from the methodology described above are provided. Again, the discussion is presented first by discussing the operational and embodied carbon footprints separately. Then those footprints are assessed in terms of the functional unit. Ultimately, the results of this research culminate by quantifying the carbon footprint of the data center based reference flow of provisioning 1 kW-year of data center capacity.

5.4.1 Operational Carbon Footprint

The first set of results reflect the operational carbon footprint of the global data center systems. Figure 5.7 shows CPU workload values for a single language at each of the data centers in the global network. The variance in the curves demonstrate the effectiveness of using the traffic coefficients. The CPU workloads are used in EnergyPlus as building plug loads that must be powered and cooled by the data center infrastructure. The EnergyPlus model performs a physics based simulation for the total building considering these CPU loads, the ambient environment, the interior operational temperatures, and systems inefficiencies to quantify the energy use for each hour of the year. The resulting energy demand of the building at hourly intervals from EnergyPlus is then passed to the DOSCOE - marginal costs of energy model. This model quantifies the data center's incremental cost of energy within it's respective power grid. The annualized carbon footprint from the MEC coupled BEM model of all the language and DC pairs are noted in Table 5.7. Figure 5.8 shows the operational carbon footprint in terms of the functional unit of 1-kW of provisioned capacity for each DC-language pair.

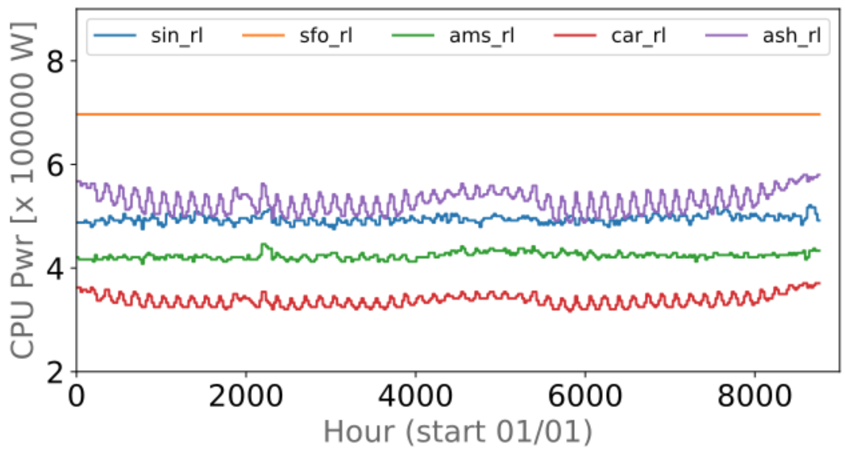


Figure 5.7: The curves indicates the CPU power demand by English language pages visits to each respective data center. The names of the curves are abbreviated for the reset load (rl) models run by Kumar in [47]. sin:Singapore, sfo:San Francisco, CA, USA, ams:Haarlem, Netherlands, car: Carrollton, TX, USA, ash: Ashburn, Virginia, USA

Site	German	English	Spanish	French	Japanese	Russian	Chinese	Total
California	0.0	$1.24\text{x}10^6$	0.0	0.0	0.0	0.0	0.0	$1.24\text{x}10^6$
Carollton	0.0	$6.59\text{x}10^4$	$1.20\text{x}10^6$	0.0	0.0	0.0	0.0	$1.26\text{x}10^6$
Ashburn	0.0	$4.38\text{x}10^6$	$8.0\text{x}10^5$	$1.17\text{x}10^5$	0.0	0.0	0.0	$1.36\text{x}10^6$
Amsterdam	$2.81\text{x}10^5$	$2.25\text{x}10^5$	$9.85\text{x}10^4$	$2.67\text{x}10^5$	0.0	$3.15\text{x}10^5$	$4.67\text{x}10^4$	$1.23\text{x}10^6$
Singapore	0.0	$3.74\text{x}10^5$	0.0	$3.71\text{x}10^4$	$3.35\text{x}10^5$	$3.91\text{x}10^5$	$7.87\text{x}10^4$	$1.22\text{x}10^6$
Total	$2.81\text{x}10^5$	$2.35\text{x}10^6$	$2.09\text{x}10^6$	$4.21\text{x}10^5$	$3.34\text{x}10^5$	$7.06\text{x}10^5$	1.25x5	$6.31\text{x}10^6$

Table 5.7: Data Center Operation Carbon Footprint (Tonnes of CO2 Emitted over the Year)

5.4.2 Embodied Carbon Footprint

The second set of results address the embodied cost of each data center using the USEEIO. In Figure 5.9 and Figure 5.10, the embodied costs of the building systems and the computer, network, and storage (CNS) systems are shown respectively. In the figures,

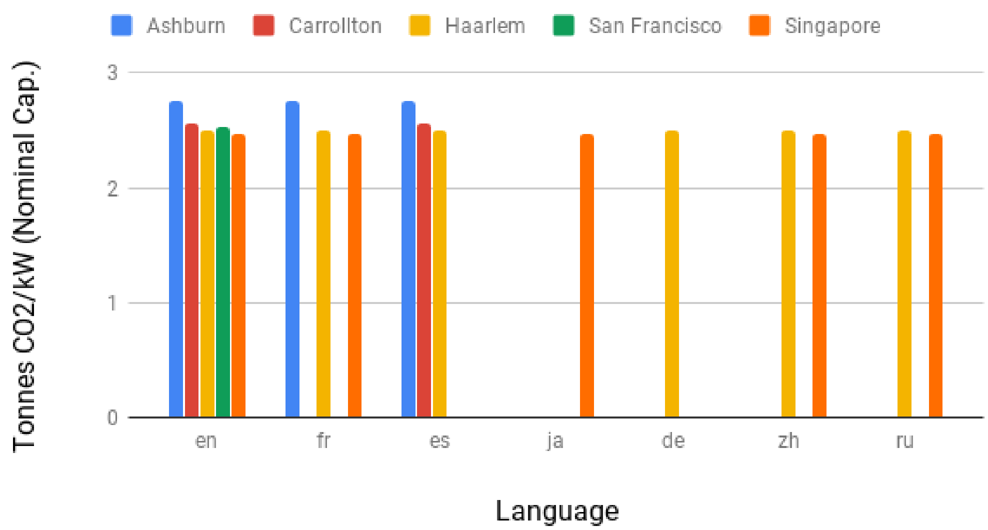


Figure 5.8: Operations CO2 per Functional Unit. The Footprint Ranges from 2.47 tonnes-CO_2 per kw to 2.75 2.47 tonnes-CO_2 per kW. All data centers yield the same carbon footprint for each kW of capacity.

the the y-axis indicates the carbon footprint of a functional unit of 1-KW provisioned DC capacity in units of CO_2 tonnes. The CNS costs reflect the embodied costs represent all SSD servers (see Figure 5.6). In comparison, the embodied costs of the IT hardware dominate over the embodied costs of the building systems. Taking the San Francisco location with a single language, the CNS embodied costs are 10 times more then the building.

5.5 Total carbon costs per functional unit

In this research, the focal point for data center sustainability is its total carbon footprint. The footprint has been quantified to the embodied values and the operational values. The total carbon footprints considering both are are shown in Figure 5.11 for each DC-language pair.

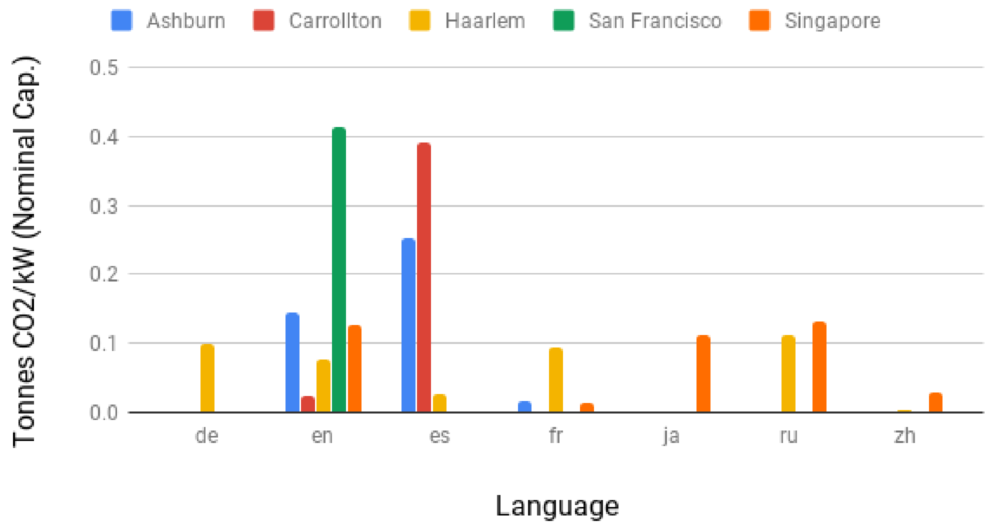


Figure 5.9: Building Embodied CO2 per Functional Unit. The building's embodied costs reflect the capacity of a language at the data center. It is apportioned by the coefficients from Figure 2.5.

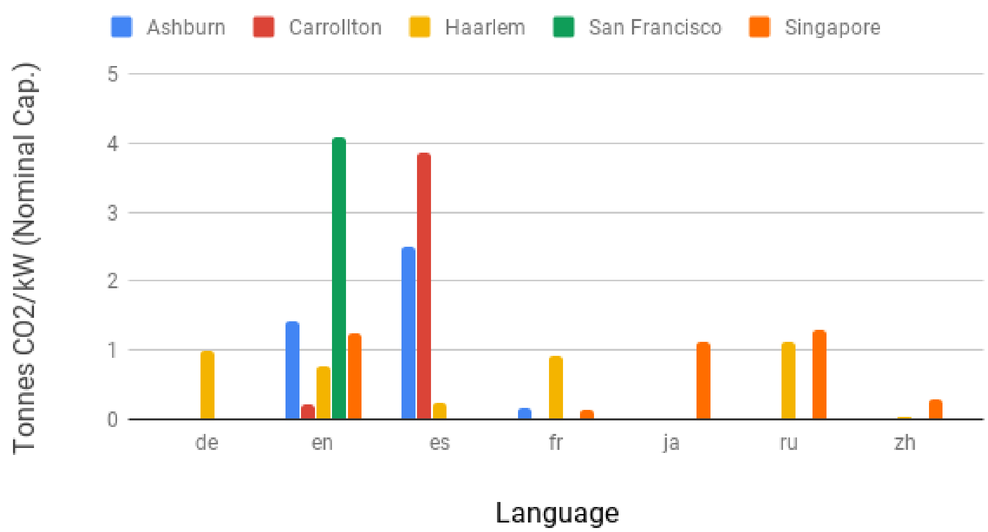


Figure 5.10: Compute, Storage, Network Embodied CO2 per Functional Unit. The CNS embodied costs reflect the capacity of a language at the data center. It is also apportioned by the coefficients from Figure 2.5. The CNS carbon density is 10 times of the building.

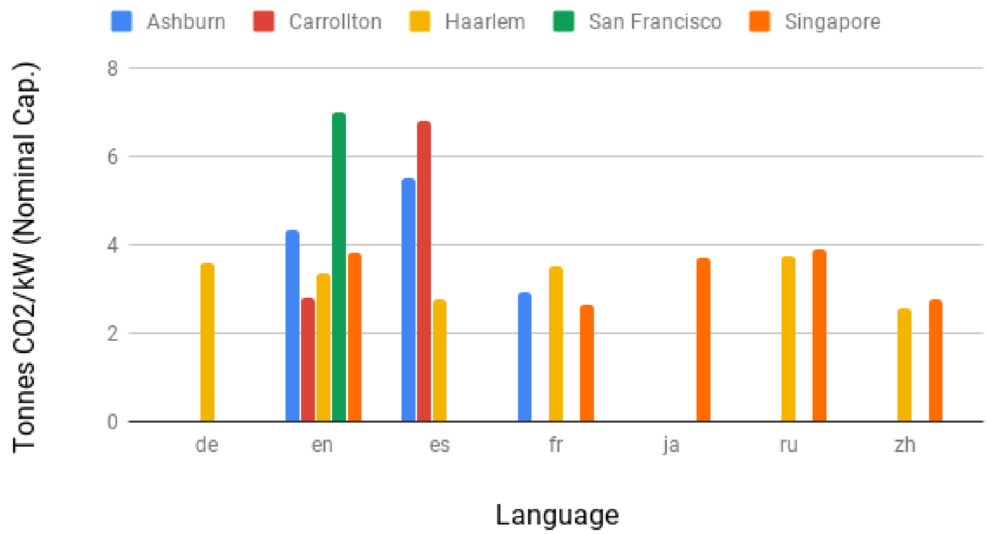


Figure 5.11: Total CO2 per Functional Unit.

5.6 Conclusion

This research coupled process and economic input-output based methods using a model that quantified the operational and embodied carbon footprint of a global network of data centers. The presented model provides two key insights. First, it showed that generally the embodied carbon dioxide of data center materials exceeds the carbon dioxide emissions during the operations by comparison of Figure 5.8 with Figure 5.11. Second, by comparison of Figure 5.9 with Figure 5.10, the model showed that with the embodied costs the CNS equipment dominate over building systems by a factor of 10X. These two insights indicate that while the focus on operational efficiency can lead to reductions in global warming potential from carbon dioxide emissions, there is still a long way to go to make data centers truly sustainable over its entire life-cycle and supply chain.

This research provides a starting point which data center architects and operators can use to assess different combinations of data center deployment strategies; addressing geographical location, network load balancing, IT hardware configurations, and building designs.

Chapter 6

Conclusions, Limitations, and Future Work

6.1 Summary of dissertation.

This dissertation has presented data centers from the researcher's perspectives as a facilities designer, hardware deployment engineer, and resource capacity manager. The data center (DC) form-factors reasoned about throughout this work are the hyper-scale DC campuses that are used for global platforms; such as search engines, social media, and public cloud services. These DCs are critical components in the daily lives of people allover, yet by design they are generally hidden from the public view. An example of the hidden critically of DCs is the on-going stay-in-place orders; which has made remote work and school over-the-internet a normal way of life for many across the world.

For the building systems community, the further proliferation of internet services will double the demands for data center facilities between 2018 and 2027. These facilities are purpose built to house information technology (IT) equipment and the utility infrastructure required to continuously operate them. Unlike many other building types, the actual operational demands of their payloads (IT equipment) are depended on external factors such as incoming network traffic. This traffic can originate across any geographical bounds from around the world. With globally sourced traffic, the cyclic week-day-hour load schedules traditionally specified in building energy models (BEM) are not sufficient to characterise the power requirement of DCs. Furthermore, as greater quantities of variable renewable energy are integrated into the electric grids, the carbon intensity values for grid power are no longer stationary. The non-stationary carbon footprint of the energy source requires coincident supply demand matching.

Given that the DC facilities and the operations account for a significant portion of an internet service's expenditures - there is a need for a programmatic framework to quantify the end-to-end costs of DCs. This research's premise is that monetary costs models are analogous to environmental costs and that the latter is more suitable for public discussions as it shields proprietary costs.

In this research, a prototype BEM framework that accounts for dynamic workloads stemming from network traffic and the marginal costs of energy in the utility is developed. The framework further extends to account the end to end costs of the system by quantifying the embodied costs of all the physical infrastructure within DCs. The results of the prototype indicate that while the operational carbon emission are significant, its the embodied costs of the IT equipment that dominate the end-to-end carbon footprint of the system.

6.2 Status Quo

Over the last decade, there have been profound improvements in the energy efficiency of data centers. The US Department of Energy summarizes the operational improvements that have led to these improvements in Shehabi's 2016 report [30]. However, the rapid improvements also come with a cost of adapting new technology; for both building systems and IT hardware. Modeling these costs is not a trivial task given the breadth of the data center systems, where several generations of technologies may co-exist in the same platform. Nonetheless, business decisions around platform placement need to be based on global costs models.

6.3 Description of Gap

To make global cost evaluations for a service platform, the inter-relationship between all of their physical resources need to be considered. For large platforms the data center costs are one of the most dominant expenditures. Within these data centers, there are three integrally coupled technical domains that influence the costs; namely building systems, IT hardware equipment, and the operational energy. In the current practice most cost modeling is typically done for each domain in isolation from one another. One exception of this is in the building design phase where the building system design and their operational energy are considered together. However, as discussed in Chapter 3 during the building design time - explicit workload profiles are typically not known.

In the current practice system cost models are done strictly from the bottoms-up for each technical domain and within strict building boundaries. It is the bottoms-up approach that leads to the facility, its IT hardware, and operational costs to being evaluated in isolation from one another and then aggregated at the global level. In realty this is a very naive approach, as the nature of globally distributed services requires coordination across all of the facilities that the platform is deployed at. For example, the need for data consistency requires that a user's change of data in one country propagates to data centers all over the world. With the inter-dependency there is a need for a modeling framework that can provide a global view of the platform operations from the top down while leveraging the granular insight that the bottoms up approach provide.

6.4 Summary of Methodology

6.4.1 Network Traffic

In order to present the workload of a data center, the researcher created a network traffic simulator based on Wikipedia's page views over a two and half year range [39]. The simulator parses the pages in the data set into their respective national languages. Then the languages are mapped to a Wikipedia data center locations based on a minimum distance function. The locations of the data centers were obtained from [41]. The segregation of the pages into languages allows them to be treated as independent online services for demonstration throughout this dissertation. As shown in Figure 2.5 there can be multiple languages routed to each data center. The simulation evaluates the relative portion of traffic that a service has at a data center for a given hour over a year. The relative portion for every language and data center pair is bound between 0 and 1, where 0 indicates no traffic and 1 indicates that all the incoming traffic to the respective data center is for one language at that hour.

6.4.2 Data Center System

Figure 6.1 indicates the layout of a modern hyper scale data-center. Several building of this size can co-exist on a single DC campus. The various fill colors indicate segregated areas that demarcate clusters or network boundaries as discussed in Section 1.8. Each of these areas span between 35,000 ft^2 to 40,000 ft^2. Supporting infrastructure spaces are indicated by the smaller areas around the cluster boundaries. In the illustrated figure, the supporting areas are primarily electrical rooms for switch gear, uninterrupted power supplies, distribution panels ,etc.

The EnergyPlus simulations in this research extended upon a publicly available data center model from Moriyama [64]. Moriyama's DC building model is annotated with dimensions in Figure 6.2. Moriyama's model represented a data center with two segregated

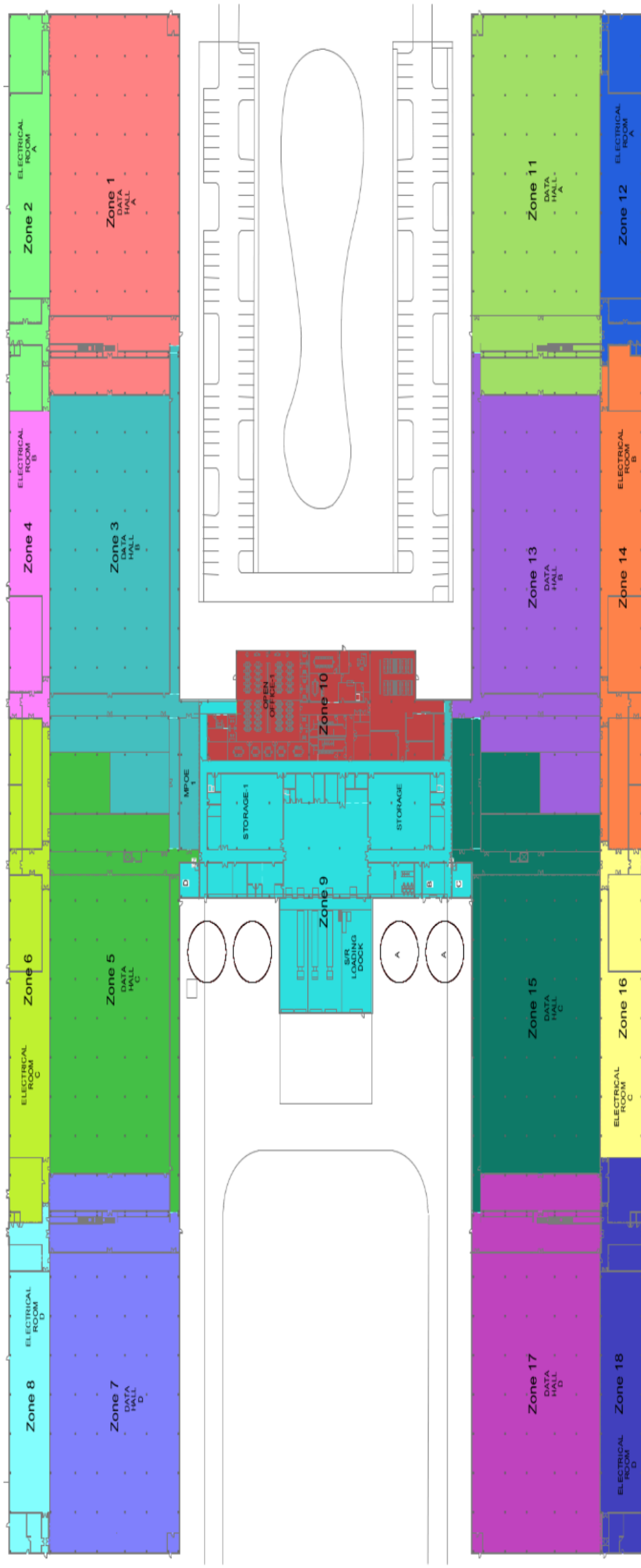


Figure 6.1: Relative Scale of Data Center Facilities compared to the EnergyPlus model used (confidential owner).

rooms summing to about 5,300 ft^2 as opposed to the nearly 360,000 ft^2 plan shown in Figure 6.1.

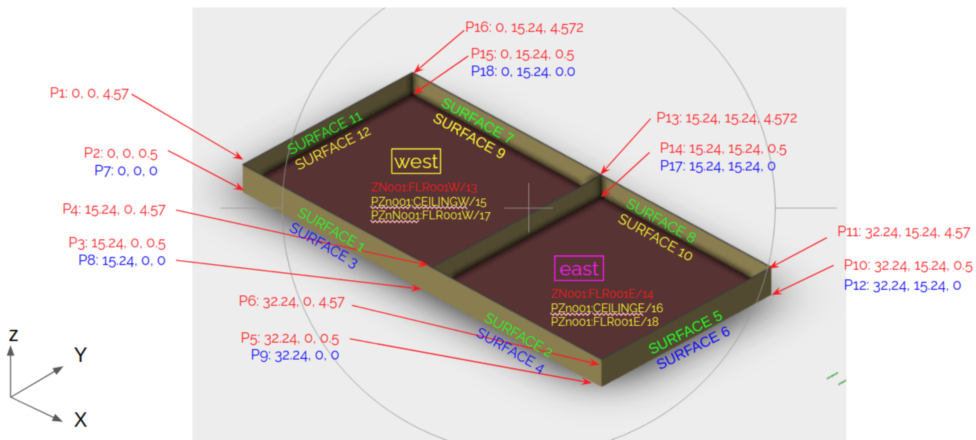


Figure 6.2: Form factor of the data center building used in the EnergyPlus models with dimensional annotations. *2ZoneDataCenterHVAC_wEconomizer*, adapted from [64].

Moriyama's model is used for the EnergyPlus simulations in Chapter 3, but the operational loads are scaled by a thousand for the DOSCOE based marginal energy costs simulations in Chapter 4 and for the embodied cost simulations in Chapter 5. This linear scaling is naive, but nonetheless it provides an indication of metropolitan scale data center deployments that exist today. Reasoning about grid profiles and network together at any resolution finer then the metropolitan area has diminishing returns as network traffic load balancing policies are typically done at the metro-level; treating the localized resources with the metropolitan area as fungible. Furthermore, as noted in Chapter 5, reasoning at this larger scale makes the grid model's result more pronounced.

6.4.3 Operational Carbon Footprint

In this research the operations carbon footprint is evaluated using two modeling steps. First, the data center building energy is evaluated as presented in Chapter 3 using the network traffic coefficient to reset the workload that a DC must support for each simulation time-step. The first model's result provides a time series of hourly demands that the data center puts on the local utility power grid. The time series demand from the building energy model is then added to the grid's demand profile as described in Chapter 4. The demand profile is simulated in the Dispatch Optimized System Cost of Energy model from Platt [57]. Platt's model is aware of the marginal carbon footprint for producing a unit of energy, accounting for the idle capacity of the power generation infrastructure. The results are indicated in Table 5.7 and illustrated in Table 6.3 below.

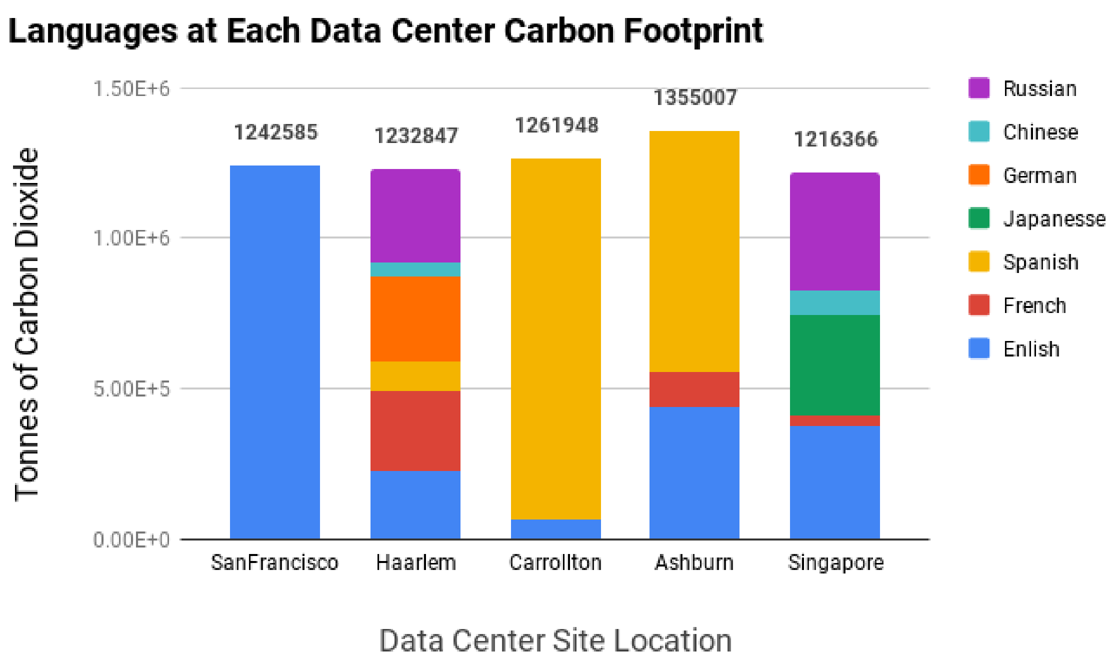


Figure 6.3: Language to Data Center Operational Carbon Footprint. The color indicates a specific language's contribution to the total carbon footprint as indicated by the height of the bar for each sites.

The functional unit of 1-kW of provisioned capacity the operation energy requirement for each DC-language pair is provided in 6.1.

6.4.4 Embodied Costs

The research used the economic input-out (EIO) method to quantify the embodied costs of the building systems [21]. As data centers were not explicitly represented in the EIO

Site	en	fr	es	ja	de	zh	ru
San Francisco	2.53	0.00	0.00	0.00	0.00	0.00	0.00
Haarlem	2.51	2.51	2.51	0.00	2.51	2.51	2.51
Carrollton	2.57	0.00	2.56	0.00	0.00	0.00	0.00
Ashburn	2.75	2.75	2.75	0.00	0.00	0.00	0.00
Singapore	2.47	2.47	0.00	2.47	0.00	2.47	2.47

Table 6.1: Operational energy's CO_2 emissions per functional unit matrix. For each Site (row) and Language (column) pair, the CO_2 density (tonnes) per provisioned kW data center capacity. Units: CO_2-tonnes per kW per year

model, an available manufacturing building was used as a baseline and supplemented with additional costs to make it more indicative of data centers as listed in Table 5.3. The EIO method was also used to quantify the embodied costs of IT equipment. The specific IT hardware modelled in this work is the SSD device as shown in Table 5.5. The relative costs indicated in the table are scaled by the nominal power capacity of the data center after factoring in the failure rates from Table 5.6.

The end result of the demonstrate framework aggregates the process based operational costs and the hybrid based embodied costs to indicated the carbon footprint per kilo-watt of provisioned capacity of the data center as indicated in Figure 5.11.

6.5 Validation

A result of the prototype, the ratio of embodied carbon footprint over operational carbon footprint is indicated in Table 6.2. The table allows the results reached in this work to be compared with past pioneers that have used other methods to quantify the carbon footprint of information technology at large scale. Masanet's seminal work considered enterprise desktop computers inclusive of peripheral devices. They found the carbon cost to be nearly even between the embodied and operational phases of the desktops. Given that Masanet's work considered office environments, the duty-cycle of the equipment were bound by the staff working hours making it dissimilar to DC's 24-hours by 7-days workloads.

Shah's works found that embodied costs contribute only 4.8% and 11.1% to the total life cycle carbon footprint for data center systems. These works aren't explicit in the derivation of the energy source's carbon intensity, but they were conducted when the renewable penetration into the US energy grid were much lower then today. Furthermore, the DC infrastructure systems were modeled with high PUE values, thus inflating the operation power of the buildings systems.

Kline's work is the most recent artifact found that assesses information technology system's life-cycle carbon footprint. Contrary to Shah, Kline evaluated the carbon footprint with a process based approach that considered the manufacturing processes for modern transistor based components. Their results paint a different picture and indicates that the embodied costs of modern IT equipment dominate the carbon footprint. They attribute their findings to the increases in transistor based components in modern IT equipment assemblies (ie SSD vs. discs), operational efficiencies from proportional workload-power control strategies, and cleaner electrical grids.

This research's results align with Kline the most in sum and across three influential things. First, the published results from embodied costs model considers servers where 72% of its components are transistor based (see SSD server in Figure 5.5). Second, the model explicitly accounts for the high rates of renewable in the grid with DOSCOE based marginal costs of energy. Third and last, the BEM model inherently reflects proportional workload-power controls.

Author	Ref.	Year	Emb-Ops Ratio	Units	Application	Embodied	Grid	Control
Masanet	[65]	2006	0.975	Mg CO2e/year	Enterprise DT	Inc. I/O	Legacy	Legacy
Shah	[1]	2011	0.111	kg CO2e	Data Center	Legacy EIO	Legacy	Legacy
Shah	[66]	2012	0.048	% (mt-CO2e)	Data Center	Legacy EIO	Legacy	Legacy
Kline	[52]	2016	1.714	t-CO2e	High End PC	Modern process	Higher Renewable	Proportional
Kumar	-	2016	1.731	t-CO2e/kW	Data Center	2013 manuf. w/ EIO	Dynamic	Proportional

Table 6.2: Comparison of results from this research with four existing literature that compared the embodied and operational costs of information technology equipment. The ratio provides a normalized means for comparison by simply looking at the relative embodied-operation per unit of measure. The evaluation compares the sum of the embodied carbon emissions across the building and IT systems and operational carbon emission due to the electricity supply to the building. Masanet results are for IT equipment in enterprise building which have lower duty-cycles. Shah's works are specific to data centers, but it based on legacy environmental costs of the EIO which don't reflect modern processes as done by Kline. Also, Masanet and Shah's models reflect legacy power grids had lower renewable penetrations, whereas Kline's results account for higher renewable energy with lower CO_2 footprint. Kline further accounts for workload proportional power. similar to the presented model.

6.6 Contribution

This dissertation developed a four module framework that's capable of quantifying the global level costs for a network of data centers leaning on the researcher's experiences at four major internet platforms. Namely, the contributions of this work are presented in the form of software modules that can be implemented completely with open source software (ie EnergyPlus, Python). The fundamental contribution of this research are listed below.

1. Candid description of data center design, deployment, and operations perspectives from hyper-scale data center experiences.

2. Building level energy model with load resets to represent real world demand profiles.

3. Marginal costs of energy for data centers that goes beyond renewable energy credits and considers the mix of dispatchable vs. non-dispatchable energy sources and includes the costs of idle generator capacity.

4. A method to assess environmental costs using EEIO on a global network of data centers using workload profiles.

5. Application of the economic input-output framework for streamlined life cycle costs assessments.

6. Culmination of the IT workloads, building energy models, marginal energy cost models, and economic input-out based models that contribute to a singular framework.

By using the proposed framework, more representative end to end costs of data centers can be assessed. In the dissertation, in-lieu of monetary costs the system costs are in terms of its carbon footprint. The framework lends itself for monetary total costs of ownership modeling of industrial applications where real costs are obtainable.

6.7 Summary of Finding

1. Cluster level abstraction suffices for building energy models - Chapter 1.
   From the researcher's observations while conducting the research, abstract cluster level decisions (i.e. SSD heavy, I/O heavy, CPU bound workloads) are long lived and high resolution specificity does not endure the test of time. The cluster level view aligns with how data center services abstract the physical implementations of their systems. This abstraction also makes it easier for building designers to reason about the systems and develop workload proportional designs in generalized terms while giving the operators the flexibility to make late binding decisions stemming from supply chain optimizations.

2. Top down network simulations indicate geographical dependencies for a network of data centers. Geographical dependency mapping is essential to understand coincident workloads and weather influences on the DC systems operational efficiencies (Chapter 2).
   Network traffic drives demand for data centers, starting from the site selection stage and drive physical mutations of the data for it useful life. The network correlation can extend to internal work generated with the data as-well by characterising the all the processes that an incoming user request generates. For mature services this relationship can be obtained from the software architecture and through empirical verification.

3. Coupling of openly available EnergyPlus with external interfaces to characterize the IT load is presented in Chapter 3.
   This allows the evaluation of coincident weather and workload that leads to identifying more representative operating points for thermo-electrical equipment (ie Chillers, Power Transformers, Humidification/Dehumanisation). Note that EnergyPlus is just one method that simulates data center operations providing a means to understand

and predict the building systems efficiency based on a workload signal. In practice, any model that is capable of predicting the building system will suffice for use in the framework.

4. Coincident energy supply and energy demand matching from DC to power grid is discussed in Chapter **??**.
   With the variability in renewable energy sources, the data center energy demands need to be matched with the generation mix for each instant of operations.

5. Hybrid life cycle assessment methods consisting of EEIO and process based approaches can characterize the embodied costs of a network of data center as presented in Chapter 5.
   The novel approach of the research apportioned the embodied costs of the infrastructure to a particular service based on its traffic based coefficient factor.

6.8 Limitations

The work has demonstrated the proof of concept for coupling a global data center network across building and technology domains using information that are publicly shareable. The method and framework is technically sound, but the rapid change in technology supporting the industry and proprietary implementation of hardware designs, building architectures, and network architecture necessitates that users of this framework characterise their own system's first. Characterising IT workloads is a non-trivial task [24], but empirical data along with understanding of logical architecture of mature services can provide sufficient results. A counter example of a matures service is the emerging increase in machine learning workloads at data centers, where the empirical based characterization of service work loads may not be adequate.

The proof of concept correlating network to traffic in practice is quite complex. For example, the traffic profile shown in Figure does not necessarily have a linear correlation with computational workloads. In practice, the traffic increase will instantiate several back-end compute processes (or jobs). Each of these process may scale at a different rate compared to the incoming traffic.

The Wikipedia simulation presented in the dissertation would model a linear relationship of those curves and power. The demonstration with that simulation presents just one dimension of several found in the software stack, in that it only considers the front end services. The curves from and the ones from Wikipedia represent front end curves - which is the users entry to the data center.

The most robust model would correlate front-end traffic to a back-end services vector for processes. The vectorized traffic profile can be treated in the pre-processing step of the modeling process and the back-end processes would each scale at a different rate with the front-end traffic.

This dissertation did not demonstrate the front-end to back-end process relationships, as it is out of scope of the work. Nonetheless, vectorizing is possible for operators if they are interested in finding out their own costs or environmental footprints. This relationship requires deep familiarity with the architecture of the service, but the framework would be similar to the one demonstrated. The only difference would be that traffic is segregated further to a specific back-end task and then aggregated down stream in the calculation as done for each data center .

The scope of the research was motivated from a building designers view. This work did not aim to quantify the micro-level life cycle impacts from individual components found in data centers. Furthermore, the physics of the EnergyPlus models representation of the IT (CPU) workloads are not critically validated. It is accepted that the IT workloads are generically quantified in EnergyPlus and in production applications explicit validation is required.

The energy grid model provided in this work is a modular component. It purpose was to demonstrate the temporal variation of the renewable sources into modern electrical grids. The energy grid model, $DOSCOE$ [57]. The $DOSCOE$ specifically accounts for the variability in renewable sources and it indicates the marginal $LCOE$ of generating the next unit of electricity at it's penetration rate, plus the $LCOE$ of the baseline. The $LCOE$ assumes that the costs of electricity is the cost capital costs of construction, plus annual fixed cost to maintain and operate the power generation plant (even if it produces no electricity), plus the variable costs to produce the electricity.

6.9 Conclusions

Modeling data centers as a global system requires characterising the full system spanning across IT and building domains. The most fundamental component is the correlation between physical resource demands and the digital information technology workloads that drive the demands. Once the workload dependencies of the DC infrastructure are established, models of the infrastructure can be simulated. This allows scenario modeling and optimization controls of the system. Given that data centers are global, there is a enormous amount of fungiblity in how the workloads can be distributed across the world. Making the models aware of the marginal costs of energy and embodied costs of the physical infrastructure are example applications of making use of workload aware building energy models in the facilities design and operations phases.

This research is the first to couple distributed internet workloads in data center building energy models with variable energy sources and embodied costs of materials in a common workflow to quantify the monetary and environmental costs of data centers. Similar works form the past were used to validate the finding of the work as shown in Table 6.2.

The three research objectives achieved through this work include the following. First, the identification of parameters that influence data center infrastructure across their useful lives. Second, the work has created a workflow that allows the coupling of all the influencing parameters that impact the life cycle costs of DCs. The final objective achieved produces simple results that are consumable by building architects, engineers, designers and web-service administrators. These simple results provide a range of values for the carbon footprint per functional unit of 1-kW of provision capacity.

Specifically the range for the total carbon footprint is between 2.75 - 6.14 tonnes-carbon equivalent per functional unit. The total carbon footprint accounts for 0.01 to 0.4 tonnes-carbon equivalent from the embodied costs of the buildings, 2.47 to 2.75 tonnes-carbon equivalent from the the operational phase, and 0.14 - 4.1 tonnes-carbon equivalent from the embodied costs of the information technology equipment.

6.10 Future Work

The research points to two interesting future research areas.

6.10.1 First: Capacity and Constraints Management

Chapter 3 provides a discussion on using the proposed BEM to dynamically reset the capacity constrain values for DC. As discussed there, the DC are a building class where its utility is measured on the power delivered to and used by the IT equipment. Opportunistic allocation of power to IT equipment has tremendous value, so pragmatically coupling this framework with cluster management software can yield 'free capacity' beyond the provisioned power capacity. This research has shown that the proposed framework can make the cluster management systems aware of capacity vs. demand at some look ahead interval, but furthermore it can support scheduling decisions based on future load profiles. The workload scheduling component of the cluster management systems can be made even more robust with day ahead extensions to the module presented in Chapter 4 to optimize future energy costs or renewable capacity.

6.10.2 Second: Optimal Control

In addition to increasing the supportable capacity of a DC, a IT load aware physics based energy model such as EnergyPlus can be used to optimize the real-time operations for the facility with the application of reinforcement learning techniques. The baseline for the model presented in Chapter 3, GymEplus, is a demonstration of such an optimized control system. While GymEplus was not targeted towards data centers, it is easy to see how the EnergyPlus model presented in this work can lend itself to GymEplus. In GymEplus, modeling the DC would entail additional state variables to the reinforcement learning environment and incorporating the reward function with an appropriate performance objective (such as presented by [67]). Going even beyond the building control optimization present by GymEplus, a reinforcement learning agent can enable traffic load balancing amongst the set of DC based on arbitrary objective function that are aware of the state of the DC characterized by the presented modules.

Appendix A

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