## Leveraging Workload Relocation and Resource Pruning for Electricity Cost Minimization in Service Provider Networks

#### PhD Thesis

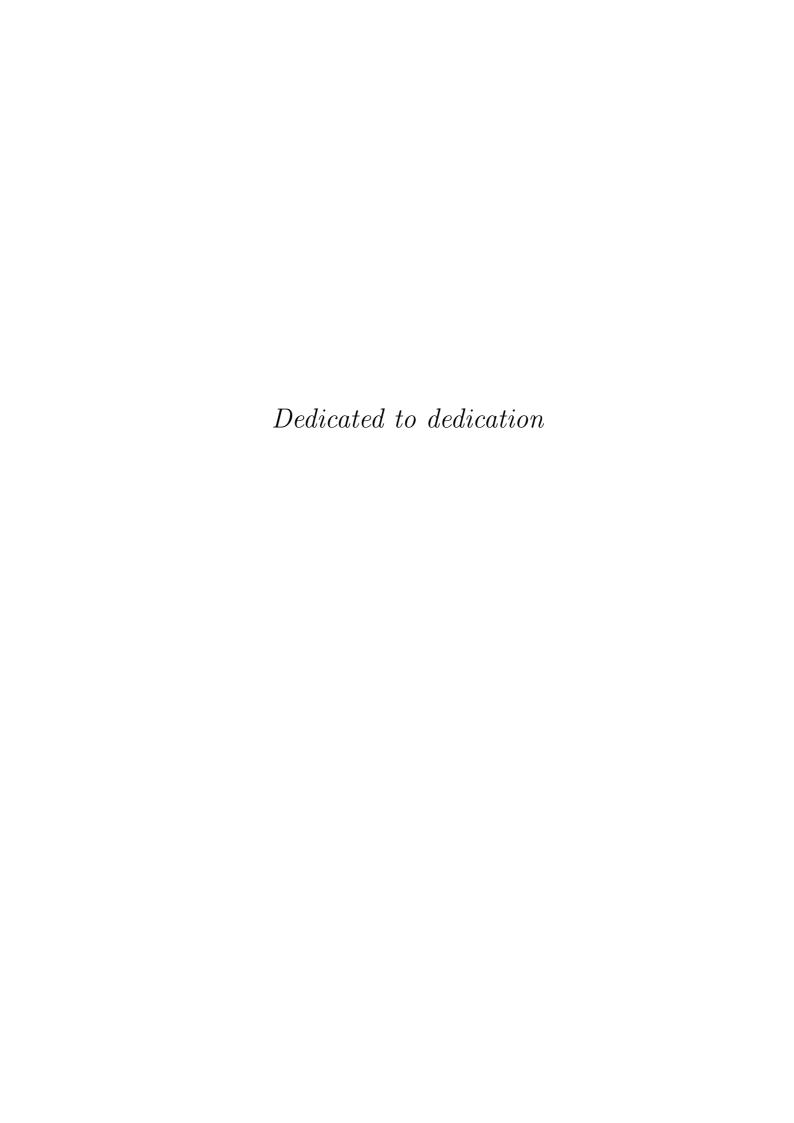
Muhammad Saqib Ilyas

2005-06-0024

Advisor: Dr. Zartash Afzal Uzmi



Department of Computer Science
School of Science and Engineering
Lahore University of Management Sciences



## Lahore University of Management Sciences

#### School of Science and Engineering

#### **CERTIFICATE**

I hereby recommend that the thesis prepared under my supervision by *Muhammad Saqib*Ilyas titled *Leveraging Workload Relocation and Resource Pruning for Elec-*tricity Cost Minimization in Service Provider Networks be accepted in partial fulfillment of the requirements for the degree of doctor of philosophy in computer science.

Dr. Zartash Afzal Uzmi (Advisor)

#### Recommendation of Examiners' Committee:

Name	Signature	
Dr. Zartash Afzal Uzmi ———		
Dr. X ————		
Dr. Y		
Dr. Z ————		

## Acknowledgements

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#### Abstract

Abstraction

## Introduction

## 1.1 Networks and systems pervade

Different types of networks play a critical role in our every day lives. We use Public Switched Telephone Networks (PSTN) and cellular networks to communicate with people by making voice calls (and sending text messages in case of cellular networks). PSTN and cellular networks also server as access media for connecting to the Internet, which offers several key services. We communicate and collaborate using email, voice/video calls over Internet Protocol (IP) and social networks. We also use the Internet to access teaching/learning material, course registration systems on campus and even pathological examination reports.

The Internet itself is an interconnection of several different types of networks. First, there are the packet-switched networks operated by Internet Service Providers (ISPs) that provide us access to Internet resources worldwide by carry information between hosts on the Internet. A second type of networks that the Internet is comprised of are the geo-diverse data centers operated by companies like Facebook, Amazon, Microsoft and Google. Servers in these data center networks run applications like Google Search, Gmail, Youtube, Twitter, Bing and Facebook. A third type of network which are also part of the Internet are the

Content Distribution Network (CDN), that place mutlple copies of Internet resources such as web pages across the globe. The role of CDNs is to keep the latency from a user to an Internet resource small (compared to having the resource located at a fixed single location). For instance, if Google's home page were only located at a server in San Jose, CA, the latency (the time it takes for a web browser to send a packet to the server) for users in Pakistan would be hundreds of milliseconds. Placing a replica of the Google home page close to Pakistan lowers the packet latency significantly, thereby allowing the web browser to display the page much faster.

The deployment of these different types of networks involves huge expenses. For instance, Google announced building a data center in Iowa at a cost of \$400 Million [1]. Furthermore, according to [2], the capital cost of a typical cellular network site is \$550,000<sup>1</sup>.

The recurring operational cost of these networks is also quite high. For instance, in 2009, Facebook spent \$50 Million on leasing the data center space, alone [3]. In the context of geo-diverse data centers, other contributors to operational expenses include staff salaries, maintenance related costs, the cost of inter-data center network connectivity and electricity bill. Similar trends may also be observed in other types of networks. Optimizing operational costs is critical for network operators in order to offer cost-effective services to consumers and maximize their profit.

### 1.2 Electricity costs in networks and systems

For many tyeps of networks, electricity costs contribute a significant fraction of operational costs. For instance, electricity costs may be as much as 15% of operational costs in data centers [4]. Similarly, for an operator with 7000 cellular sites in a country as small as Pak-

<sup>&</sup>lt;sup>1</sup>This does not include spectrum licensing costs. Furthermore, an operator needs to deploy many sites. A site at about every 800 meters is common in urban settings

istan, the annual electricity cost can be roughly estimated at \$9.19 Million<sup>2</sup>. Telecom Italia reported a consumption of 1.793 GWh in 2012 [6], which is significantly higher compared to the our estimates for the Pakistani network operator and hence the electricity costs are also expected to be much higher.

## 1.3 Energy inefficiency characterizes today's networks

For most networks, the power consumption is well-approximated as a linear function of workload [7, 8]. Furthermore, these networks are not energy proportional. In Figure 1.1, the green line shows the ideal energy proportional behaviour where the network consumes no power when there is no workload. No real network exhibits this ideal behaviour for one of the following reasons.

- 1. The network activity under no workload conditions is not significantly less than that under peak workload. For instance, a cellular network's radio components must continue operating and drawing power to offer uninterrupted connectivity to prospective allers, even when no call is in progress. In packet switching networks, many data link layer technologies continuously transmit frames irrespective of traffic activity.
- 2. The components of the network may not be energy proportional. For instance, in data centers, server power consumption is a large fraction of the total power consumption and the server idle power consumption is a large fraction of their peak power consumption.

A network that is not energy proportional is energy inefficient (i.e., consumes a lot more energy than it should) in the low-workload regimes. It has been observed for many networks

<sup>&</sup>lt;sup>2</sup>Using a 1.5 kW draw for a single cellular site [5], Rs. 10 per kWh and Rs. 100 per US\$. Note that the Rs. 10 per kWh is a gross under-estimation, given that it is the approximate current price of grid power, which is note reliable. In the absence of grid power, diesel generators power a cellular site and the resulting cost per kWh is much higher.

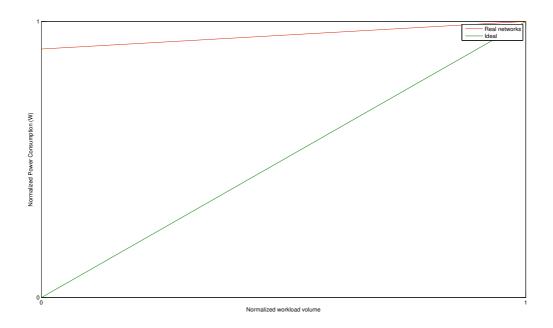


Figure 1.1: Networks lack energy proportionality

that workload is variable and periodic. Figure 1.2 shows the workload for call traffic at a cellular site in a large operational GSM network in Pakistan. It shows that call traffic has diurnal cycles and that traffic peaks for only a short period of time during a day. Furthermore, the workload peak is quite high compared to the trough. ISP [9] and data center [10] traffic also show similar trends. In order to meet peak expected workload amicably, networks are dimensioned according to the peak workload. Since the workload is far from the peak most of the time and networks are not energy proportional, most networks are energy inefficient. Recent years have witnessed significant research effort aimed at improving network energy efficiency in packet networks, cellular networks and geo-diverse data centers. Effectively, such research aims to lower the y-intercept of the red line in Figure 1.1.

We have observed earlier that network electricity costs are quite high. An energy efficient network would only incur high electricity costs if it handled a lot of workload. On the other hand, for energy inefficient networks, such as those prevalent today, high electricity costs

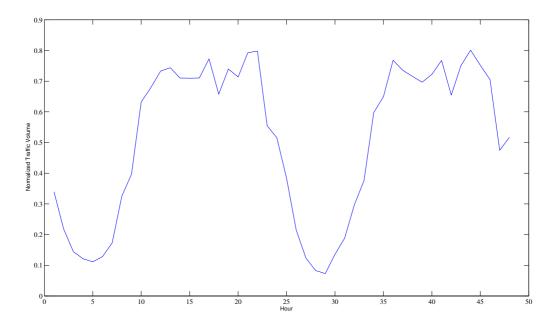


Figure 1.2: Call traffic for an opprational cellular site over two days

are not justifiable by high workload because the workload is quite variable. In other words, today's networks have very poor performance per Watt characteristics. Therefore, reducing the electricity costs in today's networks is critically important.

## 1.4 Prevalent electricity cost reduction techniques

The electricity cost for a network during a unit duration of time is given by:

Electricity 
$$cost = amount of energy consumed \times unit price of electricity (1.1)$$

Consequently, the electricity cost for a network may be reduced by minimizing either or both of the terms on the right handside of the above equation. From prior research work and current operational practices in different types of networks, we observe the following techniques to reduce electricity cost in networks by reducing one or both of the two quantities

#### 1.4.1 Reducing the amount of energy consumed

- 1. Hardware upgrades: Due to ecological challenges, improved energy efficiency is generally a key requirement when developing new technologies and devices. For a given workload demand, an improvement in device energy efficiency lowers the amount of energy consumed, thereby reducing electricity cost. Therefore, hardware upgrades are a way to reduce electricity costs. An operator would, however, opt for hardware upgrades in their network only after they have obtained the Return on Ivestment (ROI) of the initial deployment. The initial investment not only involves capital cost of equipment but other factors such as spectrum licensing as well. In the cut-throat competition prevalent in most of today's networks, the ROI is slow to achieve. This means that existing energy efficient networks would stay that way for a considerable tiem into the future.
- 2. Hardware virtualization: With the advent of ever faster CPUs, it was observed that servers tend to operate at relatively low CPU utilization most of the time. This was seen as an opportunity to statistically multiplex multiple servers onto a single physical machine by slicing the latter into multiple virtual servers. In this way, virtualization cuts capital costs for procurement of hardware. Since the virtual servers share the same resources (power supply, CPU, network interface, disks), if two servers are multiplexed onto a single physical server, the electricity consumption may be cut by as much as 50%. A more aggressive server consolidation may cut electricity costs by upto 80% [11].
- 3. Resource Pruning (RP): Since network resources must be deployed according to peak demand while the workload peaks only for a short period of time, the excess resource may be deactivated (shutdown or put in power-saving mode depending on

what is supported by the equipment) when workload is low [12, 13, 14, 15, 7]. When evaluating the reduction in electricity costs through resource pruning, it is imperative to consider any costs associated with activation and deactivation of network resources.

### 1.4.2 Using cheaper electricity - Workload Relocation (WR)

Electricity prices exhibit geographic diversity [16], i.e., the price of electricity varies from one location to another. The variation in electricity price is generally noticeable only at large distances. For instance, the electricity price anywhere within a city is generally the same<sup>3</sup>. Most networks span large enough distances for geographic diversity in electricity prices to be apparent. If the network workload is quite flexible in terms of where it is handled, then the workload originating at a location with high electricity price may be relocated to a different location that has lower electricity price, thereby cutting electricity cost. We call this technique Workload Relocation (WR). We observe that different networks have different levels of geo-flexibility in workload. In geo-diverse data centers, for instance, the workload is highly geo-flexible, i.e., a client's request may be handled close by or even hundreds of miles away. On the other hand, the workload in cellular networks has very low geo-flexibility, i.e., a call mus the handled at a cellular base station within a few hundred meters from the caller.

Electricity prices also exhibit temporal diversity [16], i.e., the relative order of electricity prices at different locations keeps changing. If a city in Kansas presently has chepaer electricity than one in Oklahoma, an hour later, the reverse may be true. This means that mapping of workload to locations must be periodically updated. The granularity of these updates depends on how frequently electricity prices change. Electricity markets exhibit price changes at two different time scales (15 minutes for real-time electricity prices and an hour for day-ahead prices).

<sup>&</sup>lt;sup>3</sup>With the exception of factors such as different tarriffs for domestic, commercial and industrial consumers

#### 1.5 Our thesis

Based on the similarity in workload characteristics and the dependence of power consumption on workload, we opine that a generalized power optimization framework may be formulated that is applicable to many different types of networks. Our generalized electricity cost optimization framework would use workload relocation and resource pruning in tandem to reduce electricity costs<sup>4</sup>.

#### 1.6 Contributions

This thesis makes the following contributions:

- We present a generalized model for electricity cost optimization applicable to different types of networks that jointly uses workload relocation and resource pruning. We show that this problem is NP-Hard.
- We present a framework called Relocate Energy Demand to Better Locations (RED-BL), pronounced Red Bull, that solves this problem. We apply RED-BL to geo-diverse data centers as well as cellular networks using real data traces.
- We exactly solve some reasonably-sized instances of this problem using real data. We also propose some heuristics that would be useful for larger instances of the problem.
- We evaluate RED-BL on two different types of networks, namely, geo-diverse data centers and cellular networks.
- Prior efforts in this area had mostly ignored the costs associated with activation and deactivation of network resources. To the best of our knowledge, we are the first to incorporate these in our optimization framework.

<sup>&</sup>lt;sup>4</sup>Hardware virtualization is complimentary to our framework

- We evaluate the benefits of geographical diversity exhibited by electricity prices and network deployments.
- A network with significant overprovisioning may handle most of the workload at cheaper locations while the more expensive ones may be pruned from the network.
   In other words, geographic diversity in electricity prices incentivises over-provisioning.
   We study the benefits of increased over-provisioning and find diminishing returns when increasing over-provisioning.

## 1.7 Organization

The rest of the document is structured as follows. In Chapter 2, we compare two different types of networks and describe how similar they are in terms of workload handling and power consumption. In chapter 3, we derive a generalized power consumption model, applicable to different types of networks and formulate RED-BL, a generalized electricity cost optimization problem. We present an evaluation of RED-BL on geo-diverse data centers and cellular networks in chapters 4 and 5, respectively. In chapter 6, we draw the conslusions about our thesis and provide some future directions.

## Background - Different Types of Networks and Their Similarities

In this chapter we look at two different network types and observe operational similarities between them from the point-of-view of power consumption.

#### 2.1 Geo-Diverse Data Centers

Data centers host applications that we consume every day. Operators such as Amazon, Google and Microsoft deploy data centers that are geographically dispersed for (i) fault tolerance (ii) low-latency to the clients.

#### 2.1.1 Structure

A really basic introduction covering: composition of a typical data center (racks, pods, networking, cooling etc)

#### 2.1.2 Request routing

front-end server based load balancing and request routing mechanisms such as IP Anycast

#### 2.1.3 Power consumption model

Describe the power consumption model from prior work and derive a more simplified yet equivalent model

#### 2.2 Cellular Networks

Just as data centers enable applications that we rely on every day, cellular networks are an important enabler of another pervasive service: telephony.

#### 2.2.1 Structure

A really basic introduction to cellular networks covering: concept of cells, mobile stations (MSs), Base Transceiver Stations (BTSs) and Base Station Controllers (BSCs)

#### 2.2.2 Call placement

How a call is handled by a BTS (at a very abstract level, i.e., how is the serving BTS chosen). Role of the BSC in cell association and call hand-off

### 2.2.3 Power consumption model

Describe the power consumption model from prior work

## 2.3 Similarities between different types of networks

Geo-diverse data centers and cellular networks are similar in the sense that both are built out of network resources to handle workload which results in electricity consumption.

# A generalized framework for electricity cost optimization

## 3.1 Modeling the electricity cost minimization problem in networks and systems

Discuss how different network types can periodically use RP and WR to minimize electricity costs. Show that this problem is NP-Hard. Describe the concept of network state and motivate a state trajectory optimization problem. Describe transition costs and formulate a mathematical optimization problem.

## 3.1.1 The objective function

Provide the mathematical form of the objective function that is designed to solve the optimal state trajectory problem.

## 3.1.2 The constraints

Comment on some of the network-specific constraints that the optimization must be subject to.

Case Study I: Geo-diverse Data

## Centers

## 4.1 Instantiating the generalized optimization formulation

Derive the objective function and constraints. Clearly outline the assumptions that we've made about the geo-diverse data centers.

## 4.2 Experimental setup

#### 4.3 Results

- 4.3.1 Sensitivity of electricity cost savings to extent of overprovisioning
- 4.3.2 Sensitivity of electricity cost savings to extent of geo-diversity
- 4.3.3 Sensitivity of electricity cost savings to magnitude of transition costs
- 4.3.4 Sensitivity of electricity cost savings to resource pruning granularity
- 4.3.5 Sensitivity of electricity cost savings to workload estimation errors
- 4.3.6 Sliding window re-optimization

#### 4.4 Discussion

## Case Study II: Cellular Networks

## 5.1 Instantiating the generalized optimization formulation

Derive the objective function and constraints. Clearly outline the assumptions that we've made about the geo-diverse data centers.

## 5.2 Experimental setup

#### 5.3 Results

## 5.3.1 Sensitivity of electricity cost savings to the duration of an optimization interval

We may optimize at different frequencies, such as once an hour or twice an hour. In this section, we study the sensitivity of electricity cost savings to the frequency of re-optimization

## 5.3.2 Sensitivity of electricity cost savings to the resource pruning granularity

We may have two states for a BTS: (i) 6+6+6, (ii) 3+3+3. Or, we may have three states: (i) 6+6+6, (ii) 4+4+4, and (iii) 2+2+2. How do the two-state and three-state resource pruning granularity settings comapre in terms of electricity cost savings?

## 5.3.3 Sensitivity of electricity cost savings to the margin of statechange damping

Suppose that we are using a two-state resource pruning model. If  $t_{max}$  is the call capacity of a 6+6+6 site, then the call capacity of the half-pruned site is  $t_{max}/2$ . If we deactivate TRXs immediately when the instantaneous call volume reaches  $t_{max}/2$ , we are likely to have many transitions due to short-term variations in call volume. We, therefore, wait until the instantaneous call volume is  $t_{max}/2 - \epsilon$  before we switch to a 3 + 3 + 3 configuration. The value of  $\epsilon$  is a configurable parameter which can take a value from 0 (very aggressive, lots of transients, perhaps more savings) to  $t_{max}/2$  (very conservative, no transients, no savings either). How do the electricity cost savings vary with the value of  $\epsilon$ .

#### 5.4 Discussion

## Conclusions and Future Work

## 6.1 Contributions

Describe the contributions made by this thesis

## 6.2 Limitations

Discuss the limitations of our work

## 6.3 Future work

Future directions

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