AN ABSTRACT OF THE THESIS OF

Fang Qi for the degree of Master of Science in Electrical and Computer Engineering presented on November 29, 2017.

Title: Improving Peak Power Shaving in Data Centers using Deep Neural Networks

Abstract approved: ____

Lizhong Chen

Data centers have been charged a great amount of electric bill by the power company and demand charge can contribute up to 40% of the electric bill due to the "random" workload. This phenomenon can be avoided by using the existing Uninterrupted Power Supply (UPS) as the assistant power source to supply the servers. The UPS will shave the peak power by supporting the servers while the peak power exceeds threshold during the on-peak duration.

For using the UPS to compensate the extra power, the problems are predicting the future data center resource usage and predicting the remaining capacity in the UPS battery. Since both problems involve in a highly correlated temporal relationship among their data, adopting Long-Short-Term-Memory(LSTM) Neural Network to perform the prediction solves the problems. After the experiment, the Long-Short-Term-Memory(LSTM) Neural Network solves the Resources Usage Prediction problem by having 6% Root Mean Square Error(RMSE) which outperforms the others and UPS Remaining Capacity achieves 7% RMSE.

Improving Peak Power Shaving in Data Centers using Deep Neural Networks

by

Fang Qi

A PROJECT

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Master of Science

Presented November 29, 2017
Commencement June 2017

Master of Science Project Report of Fang Qi presented on November 29, 2017

APPROVED:

Major Professor, representing Electrical and Computer Engineering

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Director of the School of Electrical Engineering and Computer Science

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Fang Qi, Author

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my major advisors, Dr. Chen, Lizhong for giving me such a precious opportunity to work in the world-class research facility and continues help and guidance throughout my study and research. Dr. Chen, with his always welcoming open door and wisdom advising, encourage me to continue my research against all hurdles.

I would like to thank my Committee Members Dr. Liang Huang and Dr. Mario Edgardo Magaña for constant support and guidance.

I would like to thank my research group members for their unfathomable help and suggestions.

Finally, I want to thank my parents Mr. Zhongbin Qi and Mrs. Hui Yang for their never stopped support and encouragement.

Thank you.

Fang Qi

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Chapter 1: Introduction

1.1 Why We Care About the Datacenter Electric?

As data centers' energy consumption continues to rise causing electric bills to skyrocket, more attention is being focused on reducing costs. According to the "United States Data Center Energy Usage Report" written by the United Ernest Orlando Lawrence Berkeley National Laboratory(UEOLBNL), U.S. data centers consumed around 70 billion kilowatt-hours(kWh) of energy making up 1.8% of the country's total electric consumption in 2014 [1]. By 2020, the percentage is expected to jump to 4% (73 billion kWh) according to UEOLBNL's estimates. This spike will cost data centers approximately 8 billion U.S. dollars annually in electric bill assuming constant electricity rates. For example, Google claims they consume 5.7 billion kWh in 2015; [2] which equates to roughly $600 million. Such extravagant cost has left data centers desperate to find cost and power reducing solutions.

Sizable energy consumption has another adverse effect: increasing global carbon emissions. According to [3], data centers have consumed 3% of the global electricity supply and responsible for around 2% of total greenhouse gas emissions equating the entire airline industry's carbon footprint. Climate change activists are also eager to find solutions to increase data center energy efficiency.

1.2 Challenge and Opportunity in the Data Center

To compensate for the ever-fast-growing demand and usage of the internet, companies need to constantly find ways to upgrade and optimize their data centers. Therefore, finding solutions to minimize the energy consumption and electricity bill is becoming more and more important not only request by the users but also the servers company. While at the same time the performance could not suffer major degradation due to the intense user satisfaction competition among all the large Internet company.

Data centers' available peak power is one of the main driving force to universalize data centers and enhance their computing capacity, but also is the main cost for operating expenses(Opex) and capital expense(Copex) [4]. Data centers consume a tremendous amount of electricity translating to an enormous electric bill, Lowering their consumption will not only be beneficial financially and computing resources, but will also preserve priceless natural resources and combat climate change.

Common electric bills have two charging aspects: energy consumption and power demand defined by the highest power usage of a 15-minute time slot during the whole month. The power demand portion is expensive and can be as much as 40% of the total electricity bill. Optimizing energy efficiency and reducing the power demand during the on-peak hour will dramatically reduce the electric bill.

High peak power demand can be attributed to the irregular changing workload flowing into the data center which leads to the irregular change in the computing resource usage. One way to reduce the power demand charge and avoid data center performance degradation is to use existing Uninterpreted Power Supply (UPS) to support servers during high power demand and to recharge while demand is low.

In order to use UPSs to shave peak power, solutions are needed for three problems: being able to predict future power usage, identifying the needed capacity of the UPS battery and aging cost with the known operation, and knowing how much and how long the peak power should be shaved by the energy stored in the UPS.

1.3 Contribution

To answer the three questions above, I propose the following framework which will reduce a data center's power demand and electric bill while ensuring the unchanged performance of the data center. Below is the main contribution of this Framework.

- Proposes a total resource usage predictor. It will use a long short-term memory (LSTM) neural network to predict the server resource usage of future time slots. The LSTM neural network will learn the behavior of the future data center resource usage by being fed in history data combined with the workload information and resource usage information from the Google cluster-trace data [10]. The predictor achieves an accuracy increase by 22% compared with a base model using the Linear Regression.
- Purposes a Battery Capacity Predictor which adopting the Long Short-Term Memory Neural Network which predicts the UPS battery capacity aging effect for a hypothesis operation. The LSTM neural network learns the battery capacity and aging after a hypotheses normal operation by feeding in the Li-ion battery data [11].

- Purposes a battery shaving police controller that focus on reducing the data center peak power by utilizing the energy stored in UPS battery to compensate the peak power and making decisions on adjusting the shaving peak.

The remainder report is organized as follows. Chapter 2 presents the background of data center architecture, electricity bill model, Google cluster-trace datasets and Li-ion battery sets and motivation for analyzing the peak power shaving ideal cases. Chapter 3 presents the literature review. Chapter 4 introduces the framework. Chapter 5 evaluates the framework and Chapter 6 concludes this paper.

Chapter 2. Background and Motivation

In order to find solutions to shave the peak power and reduce electricity bills in data centers, undertraining the data center architecture, especially the power usage part and electricity bill model, are the primary condition.

2.1 Data Center Architecture

According to [4], datacenters is the center of the information system; providing information service to enterprise and the public through Internet network. Being more specific, the data center is an infrastructure performing several types of data services application, using IT technology and unified standards to establish the information management system including data processing, data storage, data transmission and comprehensive analysis. The information system brings the standardization of business process and the promotion of operational efficiency to the enterprises. Data centers provide a stable and reliable infrastructure and operating environment for it while ensuring that it can be easily maintained and managed.

The first challenge faced when building a data center is the location. A variety of factors, including the company's development strategy, budget, operational cost, and safety, should be taken into consideration. Among them, communication, power, and geographical location are the three main factors when selecting a site. Since high-performance optical communication technology solves the long distance, high bandwidth, and fast transmission of information problems, service radius does not need to be considered. With access to the backbone communication network, data centers can provide services to the world.

A location's available power supply is a significant determining factor. A data center's location must be able to provide adequate and stable power. Power costs must be low because of electricity's large overhead of data centers' operating costs, Data centers have strict requirements on reliability and availability to ensure stability.

Safety is another determining factor of a data center's location. To avoid being affected by outside threats, they should be located away from any nuclear power plants, chemical plants, airports, communication base stations, military targets and natural disaster-prone areas.

A location's climate must also be considered. Cooling costs are roughly 20% of their monthly electricity bills, so choosing a cool location or place near a natural water source can lower the operating cost.

A complete data center architecture consists of three logical parts: the support system, the computing device, and the service information system. The support system mainly includes building, power equipment, environmental adjustment equipment, lighting equipment and monitoring equipment, which are necessary to ensure the normal and safe operation of the computer equipment. The computing device mainly includes the server, storage equipment, network equipment, and communication equipment. These facilities support information systems. This system is software that provides specific information services for enterprises and the public. The quality of information services depends on the serviceability of the underlying support system and computer equipment.

This paper focuses on the support system and computing device which are the main power drawers. Figure 1 shows the data center architecture and power support connections with centralized UPS. The power grid system is the data center's source of power. The high-tension electricity will go through several transformation processes to different voltages and phases to fit various electric equipment. The main power load in the data center is the lighting, office, fire emergency system, computer equipment and cooling. To ensure the reliability of the power supply to the data center, power supply system in the data center contain redundant to all the power supply equipment. As shown in figure 1, there are two diesel generators, two centralized UPS.

The computing device includes servers size scale from 5 to 100K as the computing resources. Each server mainly contains CPU, RAM, Disk, and motherboard. The computing device also includes the network gear and storage. The servers are placed onto racks and form array of racks as shown in Figure 1 as the green cycle number 7. Data centers use switches to enable the communication among all the servers, storage, and the network. The support systems are the building, power supply system, cooling system, monitoring system and lighting system, specifically to support the computing device operating efficiently and safely.

After the introduction of the architecture, component, and location of the data center, knowing the power consumption of each part of the data center is critical for lowering its electric bill. However, before that, it is important to know the power measuring method and electricity bill model. Below are parts showing how the power has been used, measured, and charged in the data center.

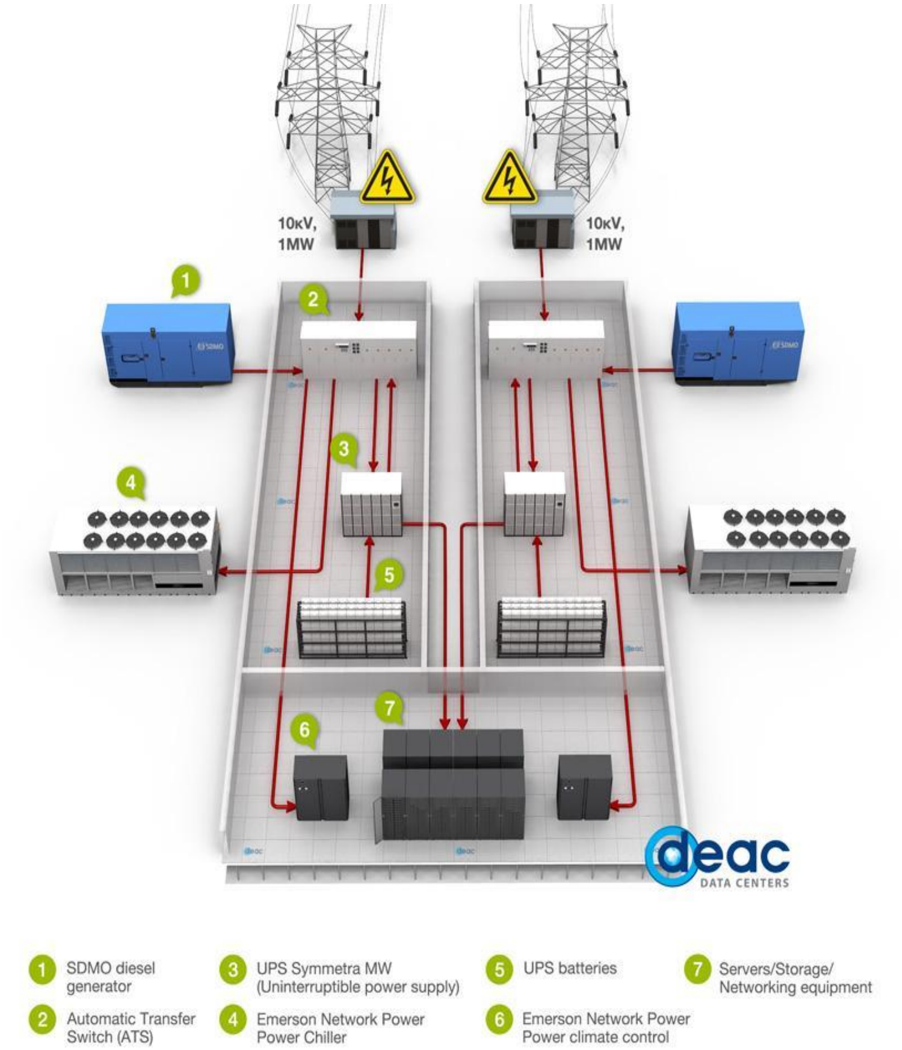

Figure 1. Data Center Architecture and Power Supply connection with centralized UPS[6]

2.2 Power Usage Efficiency (PUE) and Electricity Bill Model

Power usage effectiveness(PUE) as shown in function (1) is the most popular metric used by the data center industry to represent energy efficiency, specifically, how much energy is used by IT equipment in the duration of month or year.

$$PUE = \frac{\text{Total Power Usage}}{\text{IT Power Usage}} \quad (1)$$

When the PUE equal to 1.5, it means that there is 0.5-watt power used in cooling or maintaining whenever there is a 1-watt power used on IT side. As for showing in figure 2, Google's data center as PUE is around 1.12 which means on average, every 1 watt of IT power will need 0.12-watt supporting power.

PUE in different data centers is influenced mainly by power saving technology on the cooling side and the outside temperature. For every data center, the annual PUE is almost a fix number respect to the local weather with the condition that the power saving technology is unchanged.

Using the IT equipment energy consumption with the current PUE, the Datacenter power can approximately be determined. In other words, by reducing the IT energy (no degrade of performance), the total energy consumption for the data center will be reduced in the factor of the PUE.

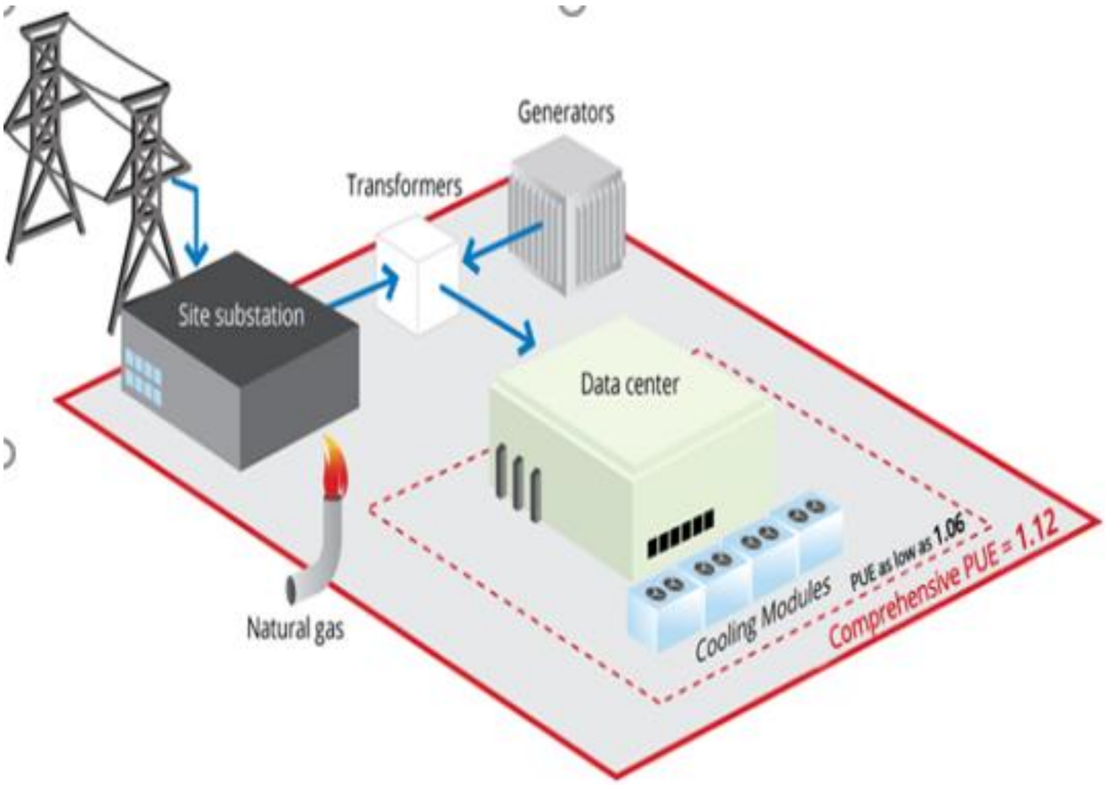

Figure 2. Google data center PUE[5]

The electric bill breaks down for data centers illustrates the main components of energy consumption with respect to the IT power. Figure 3 shown below depicts the data center energy consumption component and power loss portion. The red blocks are the overhead energy consumption component. The green blocks are the IT Energy which may also refer to producing energy. The black capital abbreviations list to the side of lines and blocks are the associated power consumption component with some representing power losses.

As shown in Figure 2 and 3, Google's data center can perform a roughly fixed PUE around 1.12. This means more than 80 percent of the power is used for computing. Therefore, any reduction of power and energy on the server-side will dramatically reduce the total power and energy of the whole data center.

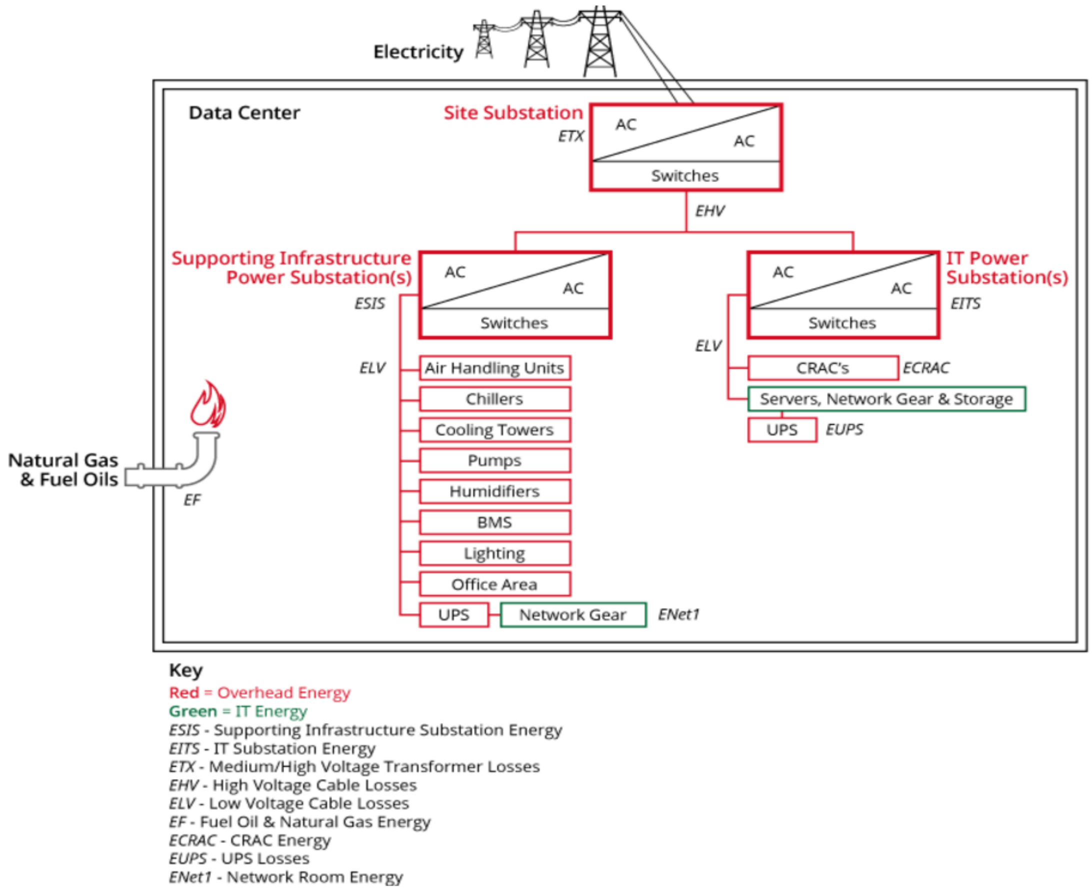

Figure 3. Google Data Center Energy usage break down and category based on Computing Energy. [5]

2.3 Electricity Bill Model

After introducing the PUE as the power efficiency measurement metric, this section will introduce the electric bill model.

As shown in Table 1, some electric companies define their pricing method as some combination of energy and power price 8]. As shown in Figure 4, energy is the integration of the power trace with respect to the whole charging period (usually a month). The green shadow shown in figure 4 gives the energy usages for a given power trace in a data center. For calculating the peak power cost, first, the electric company defines its on-peak period in a day. It will then decide a time slot unit such as 5,10,15 or 30 minutes. The company will average the power for each time slot as the red dot shows in Figure 4, which gives the peak power for every time slot. All the red dots in the month will be compared, and the highest red dot will be the peak power for that month.

Using the Duke utility company [9] as an example, the on-peak hour is defined differently for summer which is from June 1st to September 30th starting at 1 pm to 9 pm and winter which is from October 1st to May 31st starting at 6 am to 1 pm. Within the on-peak hour during a day, the electric company will define the 15 minutes to be the time slot and divides the on-peak duration into the 15 minutes slots.

Utility	Energy Cost (cent/kWh)	Peak Cost($/KW)
Duke	4.7	12
Ohio AEP	4.9	9.86
PG&E	10.8	12
Georgia Power	10.7	12.93
PEPCO	4.3	7.36

Table 1. Some Commercial US Electric Utilities Charging Table

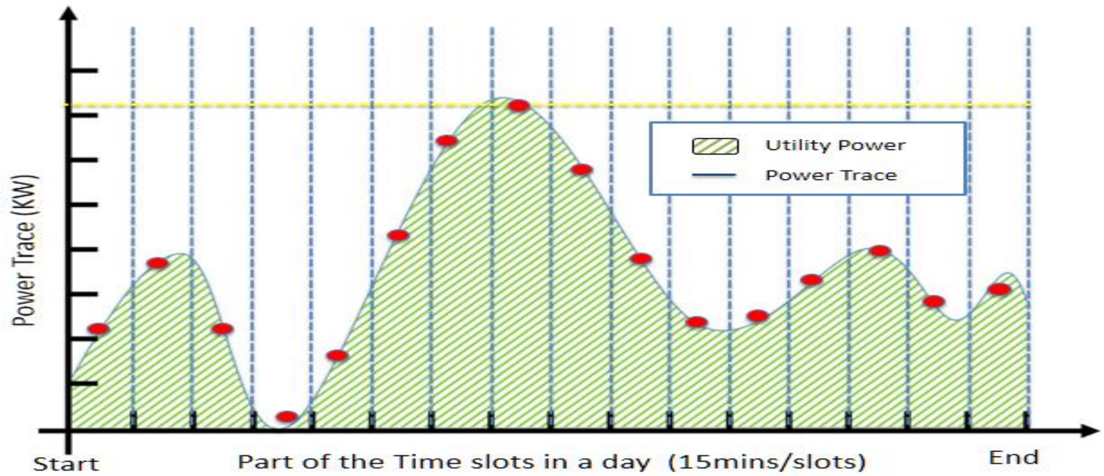

Figure 4. Data Center Power Trace and Peak Power for a Day's On-Peak Period

The power demand for a specific time slot is the average power usage during it. As shown in Table 2, the company charges on-peak power demand at $17.0920 during the summer and $10.0070 during the winter for the first 2000 kW of Billing Demand per kW, per month. The next 3000 kW will have around 2 dollars drops for both summer and winter, and for the power over the 5000 kW will again have the price drop around 2 dollars compared to the second range. With the study shown in [8], the peak power demand charge can get up to 40% to the electric bill in the data center. Therefore, finding a way to stabilize power usage and shave the peak will save large amounts of the electric bill.

On-Peak Demand Charge per month	Summer (June 1st to Sept. 30th)	Winter (Oct. 1st to May 30th)
For the first 2000 kW of Billing Demand per kW, per month	$ 17.0920	$10.0070
For the next 3000 kW of Billing Demand per kW, per month	$ 15.1619	$ 8.3356
For all over 5000 kW of Billing Demand per kW, per month	$ 12.2217	$ 6.1855

Table 2. Duke Utility Company Peak Power Charging Table

2.4 UPS Battery

After knowing the data center electric measurement method, distribution and charging model, the result for shaving the peak power will be much valuable and use the Uninterpreted Power Supply (UPS) has been purposed for years to shaving the peak power.

The UPS was initially designed to support the servers in a brief time interval around one minute during power outages until an emergency diesel generator turned on. The UPS battery can differ in structure types. One is the centralized UPS which uses Lead Acid batteries. They occupy a single room. The centralized UPS receives an alternating current and transfers it to DC current to store the energy. During the power outage, the centralized UPS battery will be discharging the stored energy in DC current and transferring that to alternating current back to the power supply unit in the data center. The centralized UPS will face two transformers and lead to two unnecessary energy lost. The other one is the distributed UPS which is frequently adopted by large company’s' data centers such as Facebook and Google. The distributed UPS used Lithium-ion battery most and placed on the server which supplies and charged to DC current with not transformation need. There is another reason makes the distributed UPS better than the centralized UPS which is the redundant problem. To increase the reliability and power support units inside, data centers need to have the redundant part which means there will be more centralized UPS and diesel generator. Adding redundant UPS is expensive not only to the data center structure space cost but also to the battery sets cost. However, the distributed UPS will not face the redundant problem due to a large amount of individual battery attached to all the racks or servers. Having few dead UPS will not hurt the reliability of the whole data center and can be taken care on the software side. Therefore, this paper will focus on the distributed UPS battery structure.

Chapter 3 Literature Review

In this chapter, the solutions to lowering the energy consumption and peak power demand charge will be introduced and analyzed.

3.1 Lower Energy Consumption

Lowering the energy consumed by all components of the data center is a major path that many scientists have been following with. They can be categorized by the target component: The server, the cooling system, and the energy producer.

For reducing the energy used by servers, turning it on and off will make a significant difference. Servers in a data center are usually in a load of 10% - 15% workload which turn-off the server to various sleep models which save significant amounts of power. However, knowing the number of servers to provide at a certain time is hard, and it is even harder to predict the needed server in the future due to irregular incoming workflow and the weak up time. As [12] described, the current way is balancing the trade-off for the energy-performance. Turning off the server while it is idle and wake it up while traffic will save energy but hurts performance.

Reducing the energy consumed to cool data centers has been the focus for the last decade. Various improvements have already been made most noticeably at Google which led to their low PUE[5]. The changes included changing the racks array into containers for battery airflow control [4], switching to cooler environments [13], and for raising the temperature inside the data center for less work on the cooling side. There is also research focused on the free cooling technology to build a data center in a cold place which uses the air outside to cool the data center [13]. However, for an existing data center, changing their current cooling system means a completely new design and potentially constructing a new data center.

Recently, the most popular solution for reducing energy costs is using green energy. Green energy such as solar, wind [14], have environmental benefits and can provide cheap power. However, the capital cost and location constraint of data centers are big drawbacks for using green energy [15].

3.2 Lower the Peak Power Demand

For the purpose of lowering peak power demand, UPS battery serves as the secondary energy source has been long introduced due to the perfect energy storage characteristic to meet the power budget. The cutting-edge technology for using the UPS energy still faces problems. As [7] described, current design about using UPS battery to shave the peak power introduces a large size lithium-ion battery and use a state machine with a fixed depth of discharge. When using a large battery, problems are the high price, large space for installing the battery and hard balance on the battery equilibrium effect. Without the ability to adjust the shaving value, the state machine policy will be vulnerable to the irregular incoming workload environment. The peak power shaving line needs a near perfect design to hold the peak power. The line will be hard to hold in the data center with the irregular workload and large amounts of servers provided. If the battery fails to hold the data center's new peak power line, then the system's benefits are wasted. If the new peak power line design is too conservative, then the peak power saving will not be the optima.

In [11], the paper introduces physical battery control policy which accurately estimates the battery. However, the control policy does not have the ability to adjust the peak power corresponding to the data center power trace to find the best net saving.

Chapter 4 Peak Power Shaving Framework

4.1 Power Shaving Approach to Ideal Case

4.1.1 Introduce the Ideal Case

The goal of this project report is to shave the peak power of data centers during the on-peak period for the best net saving. The best net saving means to know how much peak power to shave at each time. Thus, the peak shaving framework needs to adjust itself corresponding to the future power trace and battery capacity to make the smart decision to have the largest net saving.

Figure 5 shown below is the ideal case. The new peak value is suitable for the UPS battery capacity because it can shave the peak power with its own energy. The x-axis shows time that starts and end for a four-hour peak period in a 15 minute per slot fashion for a workday. The y-axis shows the power trace with the unit in kilo-watt. The solid blue line represents the power trace of the on-peak period for a regular weekday. The green shadow shows the energy supported by the UPS battery and red one shows the UPS battery charging stage.

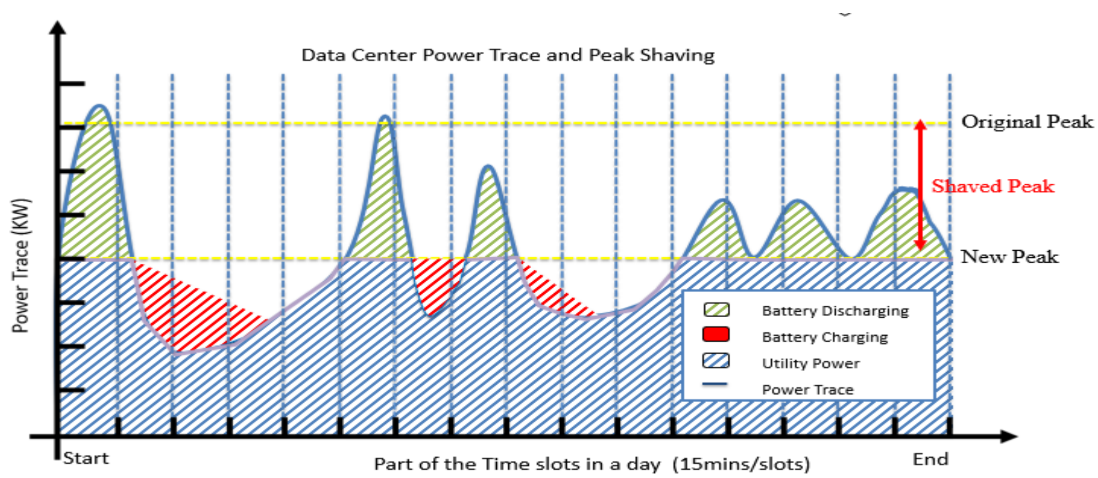

Figure 5. Ideal Case for unchanged Peak Value.

The upper yellow dashed line shows the original peak power and the lower yellow dashed line is the new peak power. For a random power trace, the new peak line means the battery can cover the energy above it, and the peak power is shaved to it. For this ideal case, the three-adjacent green shadow on the right side of the graph is the critical part which in this case determines the minimum battery size.

Figure 6 shown below is modified base from Figure 5 which increase the value of the three-adjacent green shadow on the right side. This ideal case shows that the initial new peak line is not suitable for the UPS battery which means the battery is not capable of supporting enough energy to the server due to the irregular power trace in the data center. If the new peak line does not have the ability to adjust itself, then this graph will no longer show the ideal case, and the peak power demand will jump back to the highest point of the rightmost green shadow. Since this ideal case has the ability to adjust its new peak line to a new value, the peak power saving can be promised to an optimal situation that battery capacity can support. The ability to adjust the new peak line corresponding to the incoming power trace and battery capacity is the key to approaching the ideal peak shaving solution.

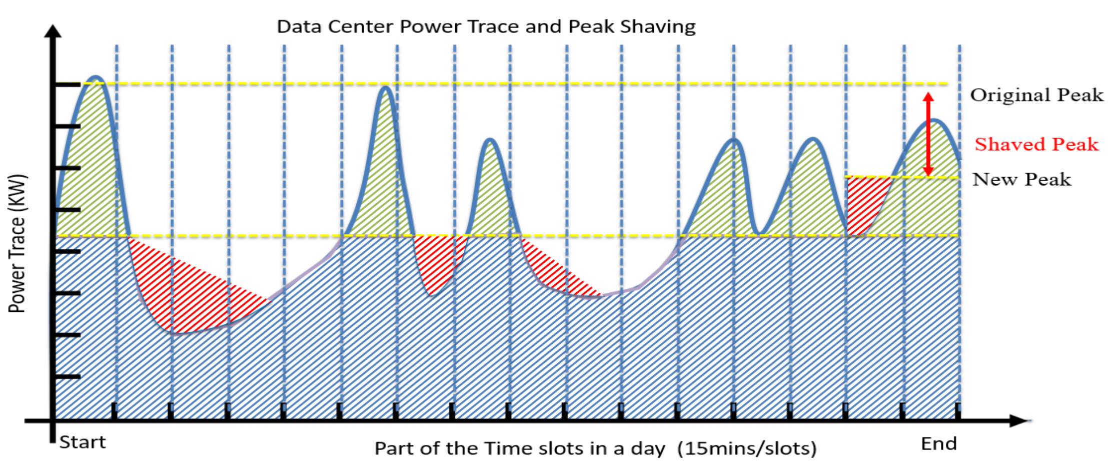

Figure 6. Ideal Case for changed Peak Value.

4.1.2 Operation Approach to Ideal Cases

As shown in figure 5 and 6, the key point behind the ideal case is to use the UPS battery to support the server while the power trace exceeds the new peak value chosen to have the best net saving for the peak power demand charge. The goal is to choose and maintain the new peak value which is difficult. However, when operating a data center's UPS to achieve the ideal case in real time, there will not have the power trace in advantage. With the operation in the real time, the real capacity of the battery used for a long time is hard to estimate accurately. Even when the battery is new to estimate the capacity well, the data center will not have the data showing the future power trace telling. Without the future datacenter power trace, adjusting the New Peak line is impossible.

Therefore, to approach to the ideal case, it is necessary to operate the data center UPS battery in real time to see how to achieve the ideal case which maintains the New Peak power line and adjust itself. As operating the UPS, assume it is the start time of the on-peak period and there is a New Peak value chosen ahead of time. Then at the time equals to the zero which means the starting of the on-peak period, there is no power trace for the future and no battery information. To maintain the New Peak Power, it is necessary to know if the energy stored in the battery is enough for pushing the peak power demand at the New Peak value. Then the prediction for both future power trace and battery capacity needs to be known. This is true for Figure 6 case as well since the prediction of the future power trace, and battery capacity is the key reason to adjust the New Peak ahead of time.

4.1.3 Optical Net Saving

The goal of this paper is to reduce data centers' overall costs by lowering the peak power demand charge. The initial cost of UPS batteries must be considered when finding a solution . Equation 2 shows that net savings equal to the saving in peak power minus battery costs.

$$\text{Net Saving} = Saving\ in\ Peak\ Power - Battery\ Cost \tag{2}$$

The costs saved by power shaving is the savings in peak power.

The objective is to know the hypotheses battery cost for comparison. Knowing the cost of the battery is a challenging case which requires knowing each hypotheses operation cost. The problem becomes even worse when accounting the irregular usages behavior and the battery aging effect. If the battery is used with no regulation, then the price for individual battery operation will not be known until the time that battery dies.

Knowing the battery cost for each operation is critical for operating the ideal case. As introduced in chapter 2, the lithium-ion battery life cycle and DoD have a direct mapping, therefore, if the battery can be set to a fixed DoD value and severing year, then the cost of each operation can be known by using the battery cost divided the life cycle for the corresponding DoD value. Additionally, since the life cycles and the serving years are fixed, the monthly or daily life cycle of the battery can also be determined.

In the end, the net saving function is presented in equation 3. The battery cost will be determined by accumulating all the cycle cost in the i-th month. And the n in the second accumulation upper bond means the battery usage cycles in a day.

$$\begin{aligned}\text{Net Saving}(\mathrm{i}^{\mathrm{th}}\ \text{month}) \\ &= Saving\ in\ Peak\ Power(i^{th}\ \ month) \\ &- \sum_{1}^{30}\sum_{1}^{n} Battery\ Cycle\ Cost\ \ (i^{th}\ \ month)\end{aligned} \tag{3}$$

4.2 Power Shaving Framework Components Flowchart

Since the key conditions for building the Power Shaving have already been discussed, the Peak Power Shaving Framework is build up and shown in Figure 7 which include the components and their flowchart. This flowchart shows its decision-making process.

The components of the Peak Power Shaving Framework are the whole data center power trace, power trace predictor, battery pack history, battery capacity predictor, and shaving policy controller. The battery usage guide is the output control command of this Peak Power Shaving Framework.

In the following sections, the component building process will be introduced including some necessary modification for the component.

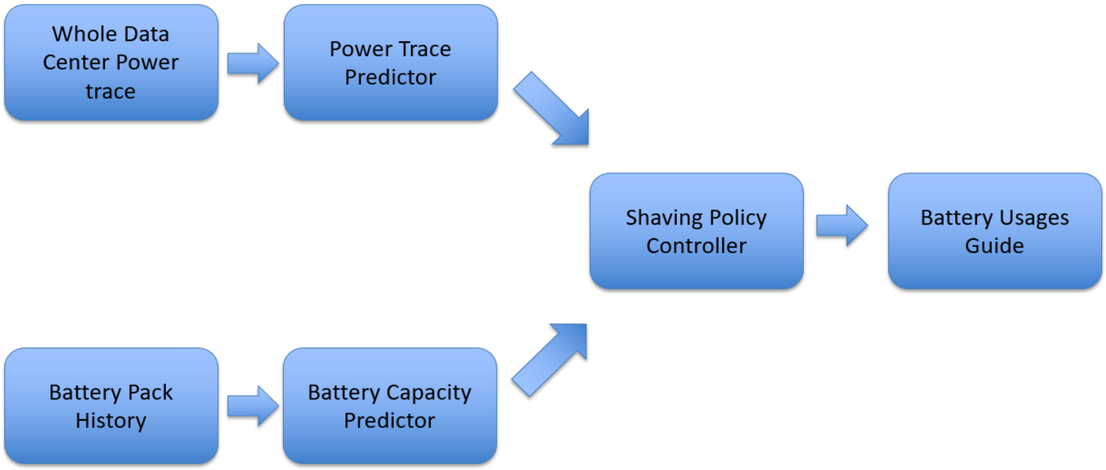

Figure 7 shaving policy flowchart

4.3 Whole Data Center Power Trace

First, introduce the whole data center power trace. This component is serving the purpose of providing data center power trace history data for later predictor building up.

The data source is called Google Data Trace [10]. As being one of the largest Internet Company in the world especially having its search engine and YouTube, the workload trace is valuable and large enough to represent a modern datacenter. The Google data center monitored in this trace contains 12.5K Servers with more than 10 different server types. The data covers 29 days of task and job level activity every server. The Google cluster-trace data consists of job_events table, machine_attributes table machine_events table task_constraints table task_events table, and task_usage table. The event tables show the incoming job workload events with their respective time, event type, job and/or task id, machine id, request CPU, RAM, and DISK. The usage table shows the usage measurement of each task in a 5 minutes period for the whole life of the task including CPU related measurement, Ram related measurement, and Disk related measurement. The task usage table is the largest and has the size of 170GB.

Google keeps this data trace in the hash and has released no information regarding the power usage trace. Therefore, there is no power trace data. However, the power trace for a data center's server group is made by the power usages for all the component inside a server which are CPU, RAM, and Disk. Knowing the usages of these resources is a good representation of the power flow in a data center. If the server model is released, the mapping between the resource usages trace and the power trace will be very easy to measure and record.

Even though we do not have the direct power trace, the resources usages trace for the whole datacenter is enough to represent the flow of the power trace. The component now will be renamed as whole data center resource usages trace.

4.4 Predictor

The predictor will predict the resource usage for the data center; the predictor is also renamed as the Resources Usages Predictor. Currently, the state-of-art uses the Machine Learning method, such as linear regression, predict the workload for a data center [17]. It only predicts the workload of a data center on the scale of seconds, which is not suitable for our application which is in minutes. And the algorithm is lacking the ability to leverage the temporal relationship of the data. Therefore, this will be a base model.

The state-of-art algorithm for prediction is deep neural networks which serve as a black box. Some uses of deep neural networks include convolutional neural networks and recurrent neural networks, and long short-term memory(LSTM) neural networks. Convolutional neural networks are famous for picture detection. They also perform well when the data has a built-in spatial relationship. LSTM is used to remember historical information and forget useless information. This paper chose LSTM algorithms to make predictions.

4.4.1 Understanding LSTM Networks

Figure 8 shows how the LSTM has the ability to update itself with information that it inherits from before. The LSTM is a special kind of Recurrent Neural Network(RNN), which can learn dependency for a long time and forget unimportant information to avoid memory explosion.

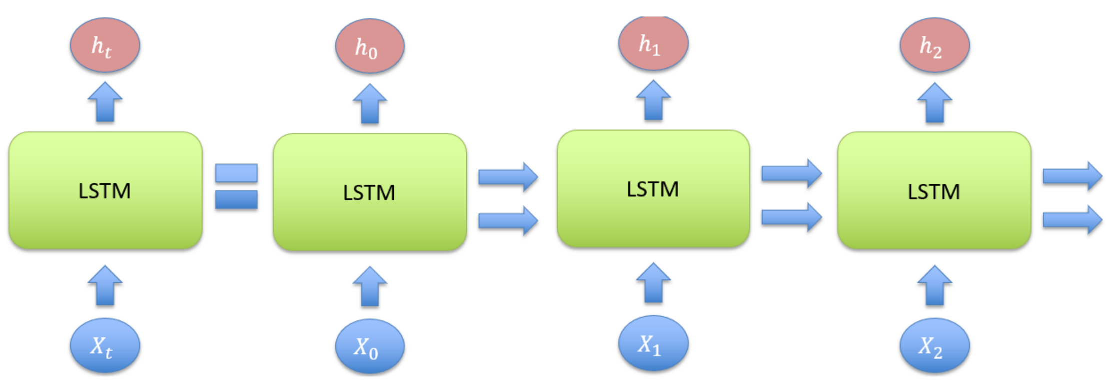

Figure 8. LSTM updating scheme

Figure 9 below shows details about LSTM inner structure. For a current operation, the LSTM will receive information from the last stage including cell and hidden information. It will combine the information between current input, last output and last cell stage to make a decision regarding what information to remember, what to forget and what to output. The yellow square named layer is the memory cell.

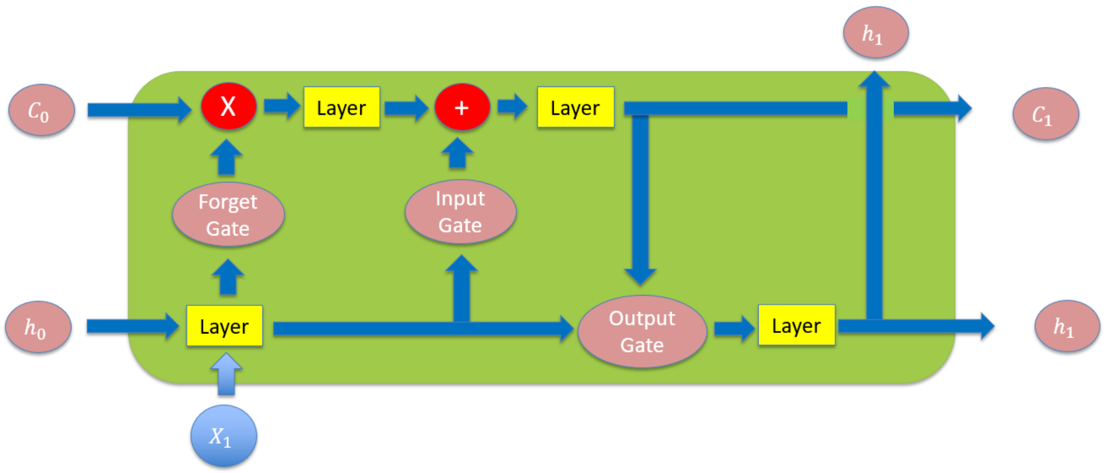

Figure 9. LSTM inner structure

4.5 Battery Data

The battery data [17] was collected by experiment on 7 different comparisons between high or low room temperatures, uniform distribution charge, and discharge or Uniform distribution discharge; Low or High probability on high discharging current.

Each testing group contains four individual 18650 battery cells and monitoring over 6 months with measurements on the power, current, and temperature every 5-10 seconds. The data was created into 19 battery state. The experiment focused on modifying irregular discharging and charging behaviors to regular Lithium-ion batteries.

4.5.1 Battery Predictor

Battery fading has a high temporal correlation in these data sets. Therefore, the LSTM will serve as the battery predictor as well. The battery data will feed into this predator and output the end voltage of the battery which can be used to determine the capacity of the battery. This process is the first of its kind to our knowledge that uses the LSTM to predict the irregular DoD battery aging behavior.

4.6 Shaving Policy Controller

Due to the fact that there is no direct mapping between source usages (CPU, RAM, DISK) and power trace for the servers in the Google data center, the shaving policy controller will only consider based cases and will not do the evaluation

The controller will determine whether to adjust the new peak line or not. It will also control whether break the Battery DoD limitation to use the remaining energy stored in the battery.

As keeping the new peak line, the beginning of the month means less cost in battery and the end of the month means the large battery cost. Therefore, if at the end of the month, the new peak line can be maintaining for just breaking few times of the DoD to use the energy stored in the battery and at the same time the net saving is high, then the controller can be designed to allow certain DoD break.

Chapter 5 Evolution

5.1 Google Data Preprocessing

In this work, the LSTM was built with Keras [19] Python Deep Learning Neural Networks library that runs on top of TensorFlow [20]. In order to train data with the Keras, the data must be in a certain form. The Google trace data was on the task and job level, and in this step, it had been converted to the task level resources usage data to machine level resources usage data and checked for integrity and consecution. The goal is to know the power trace for a data center with a certain period, therefore the old task and job level measurement data will be not suitable for this objective.

To increase the accuracy, the Google data trace is divided into 6 files according to its CPU and ram value. Therefore, for future implantation, the mapping between resources usages and power trace for the same type of server model will be available. Figure 10 shown below is the shaped data structure.

The Data structure has 8352 lines with 18 columns for every file. X features include workload account, CPU, RAM request for all the 5 minutes, and time.

Y includes average CPU or Ram usages in the 5 minutes.

$$\begin{bmatrix} x_0^1 & \cdots & x_0^{17} & y_0 \\ \vdots & \ddots & \vdots & \vdots \\ x_{8352}^1 & \cdots & x_{8352}^{17} & y_{8352} \end{bmatrix}$$

Figure 10. Modified Google Data File Structure

5.2 Battery Data Preprocessing

I chose the Uniform Distribution Discharge Room Temperature experiment which belongs to 1 of the 7-experiment group. The data has 4 battery sets.

This experiment will randomly discharge the battery at a different time and constant current. Then will charge a battery at a constant current but the random period from 0.5H to 3H.

In order to make the prediction simple, I predict the end voltage for a known operation. The X feature includes time start, time end, time steps, voltage start, current start, temperature mean, prior energy used, and total energy used. The Y is the end voltage. Therefore, there are 4 files for battery end voltage prediction. The data structure is (8352, 19) per file.

$$\begin{bmatrix} x_0^1 & \cdots & x_0^{18} & y_0 \\ \vdots & \ddots & \vdots & \vdots \\ x_{8352}^1 & \cdots & x_{8352}^{18} & y_{8352} \end{bmatrix}$$

Figure 11. Modified Battery Data File Structure

5.3 LSTM Data Converting

The training was done using Tensorflow with Keras. Keras requests the input have the same length, and the data need to be three dimensional to inherit the historical data. The data will be warped in the fashion that includes data of X and Y in the input and predicts the next output. Using the look back window equals 4 as an example. Google Trace data should look like below.

$[[x_0^1, \cdots, x_0^{17}, y_0],[x_1^1, \cdots x_1^{17}, y_1],[x_2^1, \cdots x_2^{17}, y_2],[x_3^1, \cdots, x_3^{17}, y_3]$

$[x_1^1, \cdots, x_1^{17}, y_1]$,$[x_2^1, \cdots x_2^{17}, y_2]$,$[x_3^1, \cdots x_3^{17}, y_3]$,$[x_4^1, \cdots, x_4^{17}, y_4]$

$$\vdots$$

$[x_{8348}^1, \cdots, x_{8348}^{17}, y_{8348}]$,$[x_{8349}^1, \cdots x_{8349}^{17}, y_{8349}]$,$[x_{8350}^1, \cdots x_{8350}^{17}, y_{8350}]$,

$[x_{8351}^1, \cdots, x_{8351}^{17}\ y_{8351}]]$

$$\begin{bmatrix} y_4 \\ y_5 \\ \vdots \\ y_{8351} \end{bmatrix}$$

5.4 LSTM Network Structure

The figure 12 shown below is the structure used in this work that. It has multiple LSTM layers and is connected to a regression model.

The LSTM Network will first take in the information for the first sample including the y value for the first sample, then the second to fourth sample with their y value will be feed in serious and predict the fifth y value. This process repeats until reaching the end of the data.

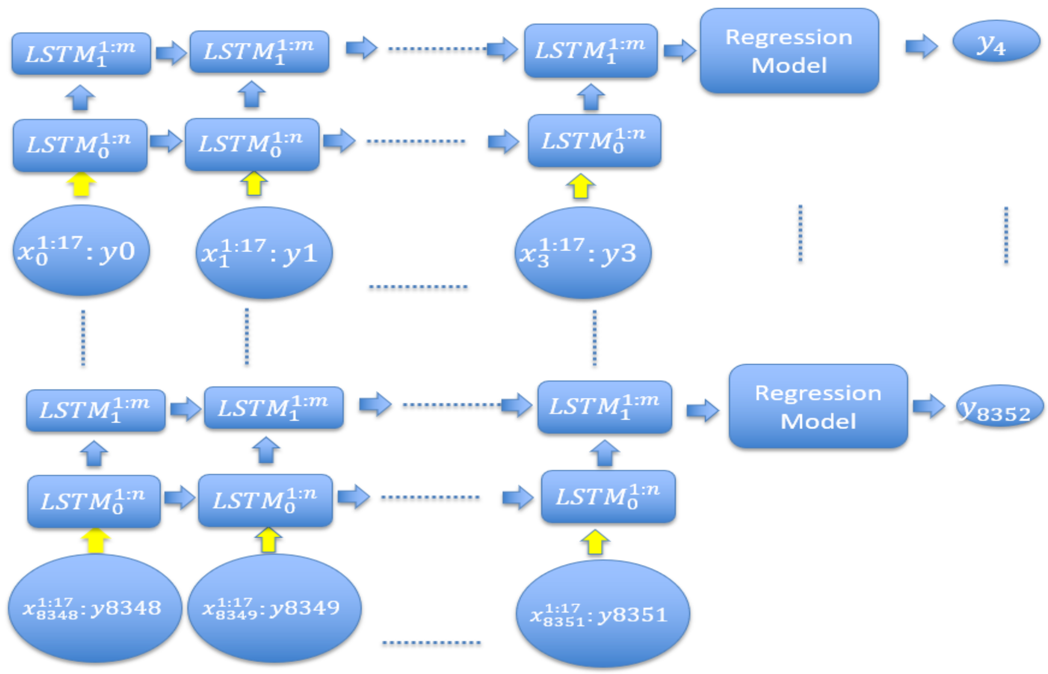

Figure 12. Deep Neural Network structure for the Predictor

5.5 LSTM Result on Google Trace data

As shown in figure 13, below is the testing result for Google Trace Data using LSTM. The Mean Square Error for both training and testing data is 0. And the Root Mean Square Error is 0.6 for training part and testing part. Comparing to the linear regression algorithm base model, the training score of LSTM is 0.11 higher for MSE and 0.16 higher for RMSE, and the testing score is 0.14 higher for MSE and 0.22 higher for RMSE.

This improvement is related to the LSTM structure that can remember important historical information and learn the principle based on it. From this accuracy, it can be concluded that the resources usages in the data center for the future 5 minutes are highly dependent on the past workload accounts, CPU request, ram request, and the resources usages history.

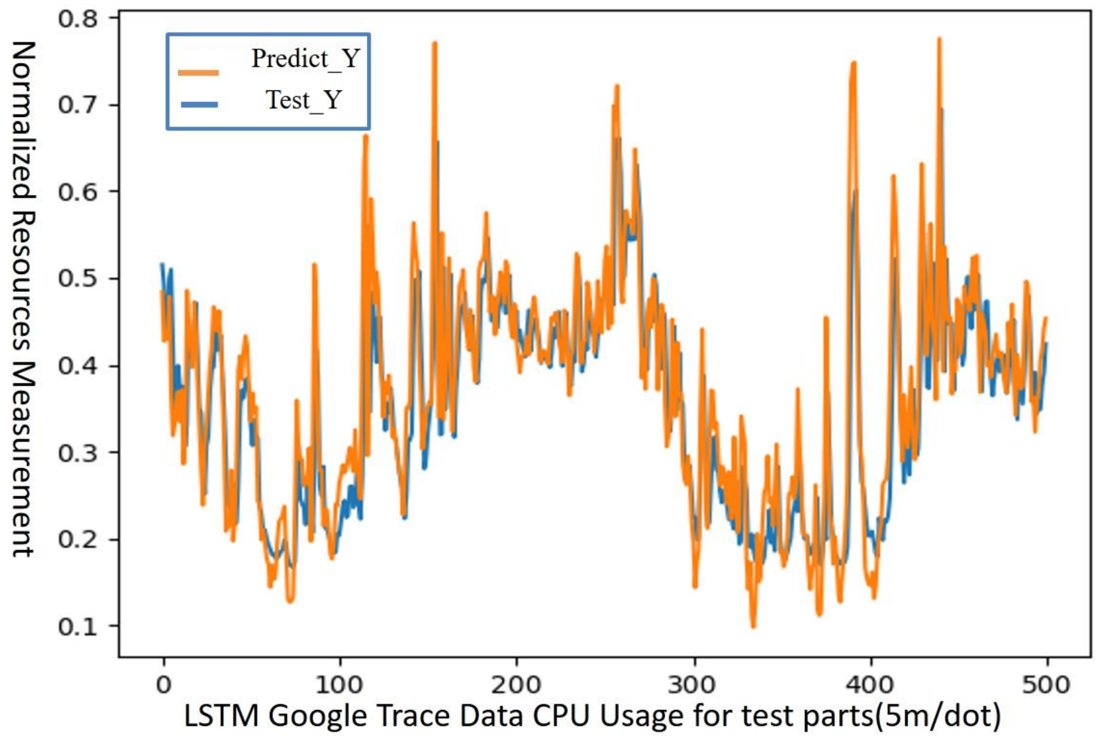

Figure 13. LSTM Prediction Accuracy for Google Cluster Data

5.6 LSTM Result on Battery data

As shown in figure 14, below is the testing result for battery data using LSTM. The Mean Square Error for both training and testing data is 0 and 0.01. And the Root Mean Square Error is 0.07 for training part and 0.09 testing part.

From this accuracy, it can be concluded that the battery capacity fading can be captured accurately using the LSTM algorithm with irregular charging and discharging behavior.

In the middle of figure 14, the orange line does not flow the two cases where the blue line jumped above the 1.0 normalization value. Since the 1.0 means the 4.2 voltage of the battery, that two blue value must be mistakes and the LSTM is smart enough not to follow the fault value.

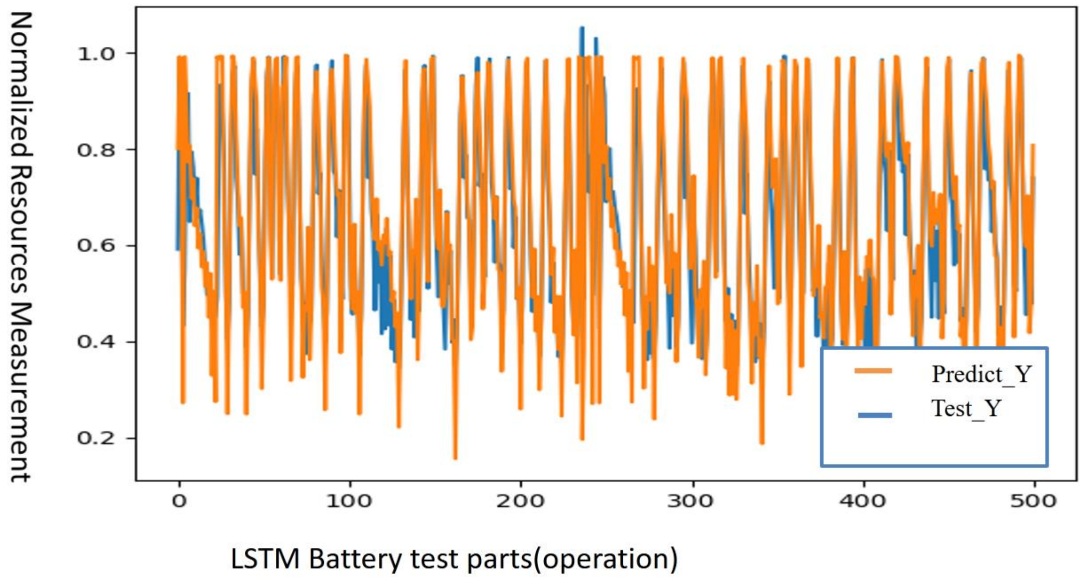

Figure 14. LSTM Prediction Accuracy for Battery Data

Chapter 6 Future Work

This work focusses on predicting the resources usage of the data center in a five minutes time slots and predicting the battery end voltage. Therefore, for the future work, there are more implementations we would like to work on, which will be listed below:

- Predict the resources usages and power trace in the data center.
- Build a deeper model to break the five minutes prediction limitation. The goal is to predict the future resources usages, power trace, and battery end voltage at least for the next fifteen minutes.
- Predict the battery capacity from the end voltage or directly predict from the battery history information.
- The accuracy model can shift the focus to the upper accuracy because the power exceeding the peak value line is more important.

Chapter 7 Conclusion

The solution to the current UPS problem has been defined and evaluated. Without the ability to adjust the New Peak line, the expensive UPS battery will not be fully utilized.

In this work, the Peak Power Shaving Framework has been established for adjusting Peak Power to achieve best net saving. The consisted components of the Framework has been well discussed with some necessary modification.

In this work, the LSTM Neural Network has been adopted to predict the Data Center Resources Usage and achieve an accuracy increase of 22%. The LSTM Neural Network has been adopted to predict the Li-ion Battery Capacity and achieve an accuracy of 0.09 RMSE.

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