OPTIMIZING BATTERY CONSUMPTION OF EDGE IOT DEVICES

by

Mujahid Khan

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Committee Members:

Dr. Anne Hee Hiong Ngu, Chair

Dr. Byran Gao

Dr. Qijun Gu

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DEDICATION

I dedicate this project to myself. A special feeling of gratitude to my loving self for enduring the mental stress over the course of the past three years. GGs only. We do not go again.

ACKNOWLEDGEMENTS

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ABSTRACT

Recent advances in the world of IoT have significantly improved what one can do with the help of personal gadgets such as smartwatches and other edge devices. This improvement has lead to the inclusion of additional functionality like fall detection, temperature and motion sensing etcetra. Although this in itself is not a bad thing, however, this does pose the problem of increased energy consumption on devices which are already constrained by limited battery. We present our study which discusses the possibility of optimizing energy consumption for edge IoT devices by reducing communication cost of applications by determining an optimal chunk size. We present a metric **energy-per-byte** or **EPB** which helps determine the optimal chunk size for respective edge devices. We evaluate our approach with the help of two case studies using different edge devices and applications, and we achieve considerable energy optimization depending on the app functionality and the hardware involved.

I. Introduction

In the past couple of years, IoT has made significant progress. From personal devices such as smartwatches and environment like smart homes, to industrially scaling projects like smart cities and smart, autonomous cars. There has been an extensive application of IoT edge devices to an extent that today, a considerably significant amount of people possess at least one such device —be it your smart car or a smartwatch that you regularly or routinely use.

Recent advances in the world of IoT have increased the amount of use cases that these personal devices such as smartwatches have. But having additional functionality also poses the problem of increased energy consumption on devices already constrained by limited battery. For example, a device logging sensor data, say temperature, in real-time is bound to use more energy if it starts logging data from a motion sensor as well.

This work studies the possibility of optimizing energy consumption for edge IoT devices by aiding the programmer in setting parameters that would ultimately lead to lesser energy consumption. We aim to focus on optimizing the communication cost of applications by determining the optimal chunk size, with which the data should be transferred. It also involves a case study comparing energy consumption of native app and the same app running in a container environment such as Docker (cite here).

There has been an extensive amount of work on energy optimization —both without and in an IoT setting. Xiao et al. [5] compared 3G and Wi-fi while Balasubramanian et al. (cite here) compared GSM, 3G and Wi-Fi with respect to energy consumption. However, neither of them compared energy consumption of respective data transfer technologies for throughput efficiency for the same task.

Gupta et al. (cite here) made a measurement study of energy consumption

when using VoIP applications with Wi-Fi connection in smartphones and showed that power saving mode in Wi-Fi together with intelligent scanning techniques can reduce energy consumption. Xiao et al. (cite here) measured energy consumption for video streaming on mobile apps and concluded that Wi-Fi is more efficient than 3G. There are other measurement studies as well which compare different modes of communication but none of them discuss energy consumption differences for different packet sizes.

The work that seems the most related to ours is by Friedman et al. (cite here) where they measured power and throughput performance of Bluetooth and Wi-Fi usage in smartphones. They concluded that power consumption is generally linear with the obtained throughput, and Bluetooth uses less energy than Wi-Fi. However, this study also showed that different hardware and different software have different results and there is no generic trend. They also concluded that an upper bound does exist, bottlenecked by the receiver, after which the sender expends more power retransmitting packets. This dependency of energy consumption on software is also discussed by Flinn and Satyanarayanan (cite here) who point out that "*There is growing consensus that advances in battery technology and low-power circuit design cannot, by themselves, meet the energy needs of future movile computers* "(cite here). This observation has been confirmed by recent advances in green software engineering, which demonstrated how the source of energy leaks can be software-related as well (cite here).

Our work on the other hand, considers multiple constraints in real-world IoT setting. Firstly, the transmission is not always continuous. The data may be communicated in regular or irregular intervals. Secondly, the amount of data to send depends on the amount of data collected by the sensors which may vary based on different applications. Thirdly, since the transmission may not be continuous, if the app demands it, based off energy consumption data from different chunk sizes, an

optimal communication interval can be set to reduce the amount of buffering required (if needed). Lastly, unique apps on different devices with different operating systems will have their own optimal throughput efficiency for energy consumption. Given the hardware configuration of such a device, our tool can determine the optimal chunk size for data transfer with respect to energy consumption.

I.0.1 Contributions

This thesis has the following contributions. It:

- proposes a method to estimate energy consumption of edge IoT devices
- proposes a new approach to reduce energy consumption with the help of optimal chunk size
- presents a new metric called Energy-Per-Byte or EPB
- discusses a case study to compare energy consumption between native, Lingua Franca and container version of the same app.
- evaluates the effectiveness of this approach on two real-world applications of different domains.

The organization of the rest of the thesis as as follows. In chapter II, we will provide background information about edge IoT devices, energy usage and optimization, containers and middleware accessor frameworks. In chapter III, we briefly summarize the related work and chapter IV will discuss our methodology in detail. In chapter V, we will discuss our evaluation and results, and provide our reasoning. Chapter VI, will discuss the case study of energy cost comparison between native, Lingua Franca and Docker version of the same application and finally in chapter VII, we will conclude our thesis and discuss possible future work.

II. Literature Review

Over the past few years, Internet of Things or IoT, has had a significant impact in our lives. It plays an important role whether it is a smartphone or a smarthome environment or just something as handy as a smartwatch. Different types of data is collected and exchanged among interconnected sensors/devices through modern communication network infrastructure connected by million of IoT nodes [6, 7, 8, 9, 10]. This direction of computing has already overtaken the traditional methods based on stationary computing [11]. As a paradigm, IoT expresses that most physical devices, such as smart phones, smart watches and other embedded devices are interconnected with each other. These devices communicate with data centers and exchange information —all while adhering to their routine tasks [8].

Following various popular technologies these days, such as smart homes, smart grid and smart healthcare, IoT has become one of the essential components of people's home and workplace existence. It will continue to impact the daily life of people and its not just limited to technology. IoT has been reported to be one of the most important technologies that will impact US interests in 2025 [8]. The number of interconnected physical devices has already transcended the human population for a couple years now. In 2012, there were 9 billion interconnected physical devices [11]. This rapid increase in the number of mobile devices suggested that conventional centralized cloud computing would struggle to satisfy the Quality of Service (QoS) for many applications. However, with the introduction of 5G technology, edge computing becomes a viable and key solution to solve this issue [12, 13, 14]. The edge computing platform allows edge nodes to respond to service demands which results in reduced bandwidth consumption and network latency. Figure 1 shows a basic edge computing architecture.

Edge computing based IoT helps solve some critical issues and improves

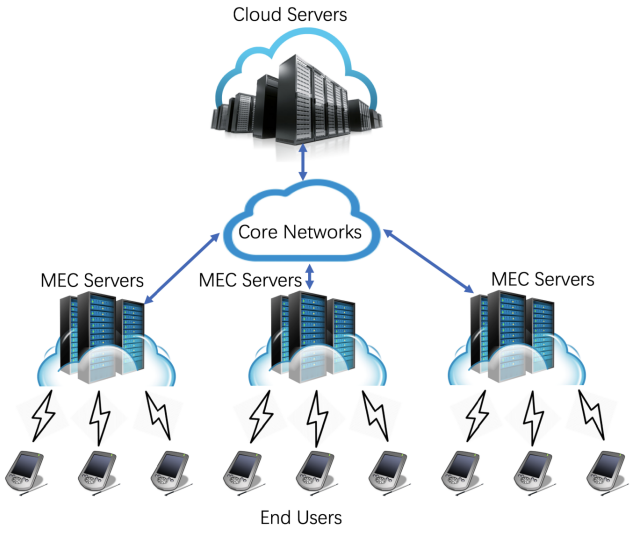

Figure 1: The basic edge computing architecture

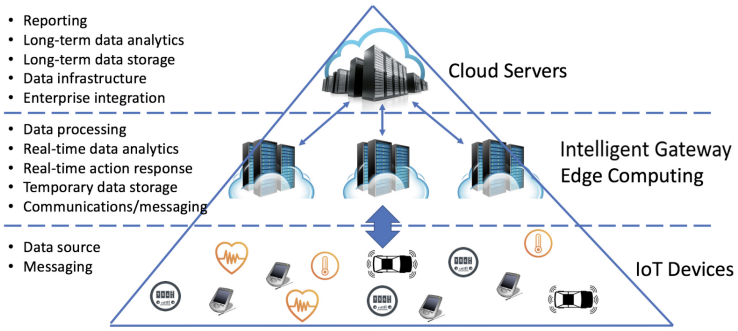

Figure 2: Edge computing based IoT architecture

performance. Not to mention, IoT and edge computing share some characteristics which is further clarified by figure 2.

It further illustrates that IoT devices are end users for edge computing and IoT can benefit from both cloud and edge computing. The latter helps with faster response times and provides a tolerable computational capacity and storage space. Nowadays, the physical end user devices such as smart phones are considered edge devices. They may have an exclusively local component of an application but most generally, some sort of data is communicated with the cloud server, with or without

the help of a gateway device.

One of the restricting factors among IoT edge devices is limited battery life (among limited storage and other things). Even though IoT and mobile devices are enabling a connected future that promises huge amounts of time and money saved with better automation, control in industry and our everyday activities, as well as other benefits such as better health care via remote monitoring and efficient fuel usage in smart and increasingly autonomous vehicles [1], it is a matter of fact that amongst these are portable devices which require a battery to operate. Usually, these devices have small form factors which limits the size of battery that can be used in these devices. There haven't been dramatic improvements in terms of alternative, more reliable battery types which in turn limits the capabilities of components in such edge devices. Figure 3 shows a breakdown of average energy usage across 1520 users of Samsung Galaxy S3 and S4 mobile devices [1]. In this experiment, users were divided into five groups based on their activity levels. It shows that each group of users has varying needs for which respective hardware component consumes more energy. In the recent years, there has been a strong motivation to minimize energy and power across all of these components so that mobile and IoT devices last longer on a single charge, and to also allow more sophisticated components such as CPU, GPUs and NPUs [1].

This need of minimizing energy consumption of such devices had lead to a plethora of techniques being developed to reduce the overall energy consumption of edge devices. Researchers have used machine learning approaches to categorize applications during execution and choose a suitable pre-existing power plan [15, 16, 17]. However, it was later realized that this does not capture dynamic workload variations [18]. Later on, a new technique was proposed which involved phase level instrumentation to collect workload statistics at runtime. Essentially, the worload was divided into snippets and performance application programming

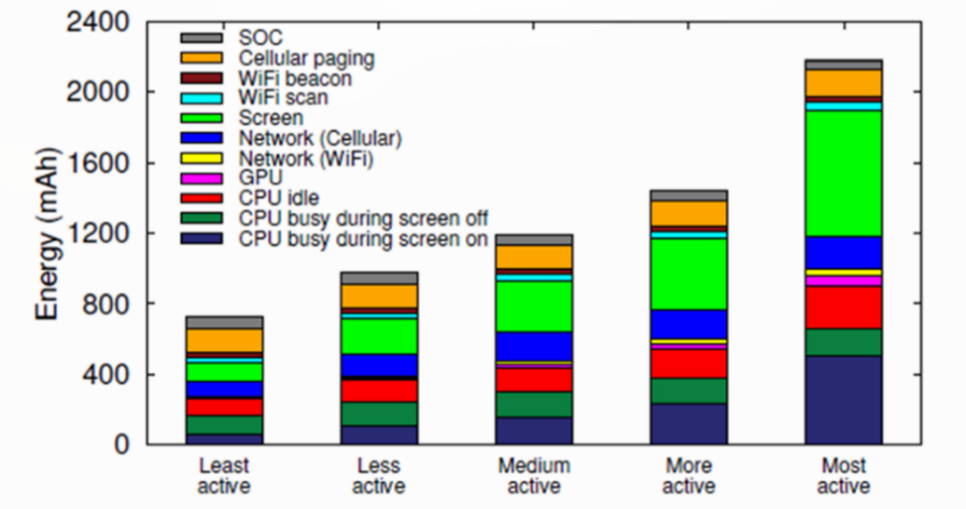

Figure 3: Average daily energy drain breakdown of 5 groups of 1520 apps [1]

interface calls were inserted between each snippet. The data collected from each snippet was then used to control the power states of processing elements [19]. There are other ML based approaches as well where some are better than the other using Reinforcement Learning and Imitation Learning [20, 21, 22, 23, 24, 25, 26]. Other than display optimations [27, 28, 29], wireless radio optimizations [30, 31, 32, 33, 34, 35] and main memory optimizations [36], there have also been software and user-centric optimizations. A variety of OS level energy management techniques have been proposed in literature [37, 38]. Runtime software profiling can identify the most power and energy hungry resournces that should be targetted by dynamic managament techniques. Powerscope [39] is one such example of a tool. It maps energy consumption of active applications to program structure. It further combines hardware instrumentation to measure current levels with kernel software support to perform statistical sampling of system activity. For mobile devices, the display is the main user interface. User satisfaction is directly impacted by brightness and content on the display. CAPED [2] uses an online learning algorithm that dynamically controls the display brightness to meet individual user's

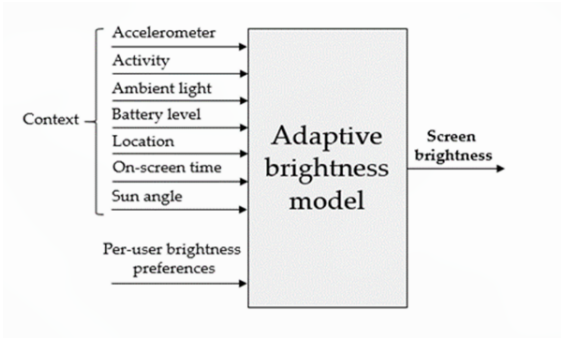

Figure 4: Online learning control of display brightness [2]

preferences. Figure 4 depicts how CAPED's online learning control works.

Virtualization is commonly defined as the act of creating a virtual version of something, including but not limited to, hardware platforms, storage devices and network resources. It has many advantages including flexibility, capacity, processing power, growth in demand, and energy efficiency [40]. A virtual machine instance represents an entire isolated environment. Multiple isolated environments can run and multiplex the resources of the same host. However, a new model has emerged which has been quite in demand for the past couple of years. *Containers* [41] allow multiple user-space instances and are generally lightweight. They have limited overhead compared to Virtual Machines (VMs) and unlike virtualization, paravirtualization or full virtualization, they do not require an emulation layer to run. Instead they use the host OS [42]. One such notable example of a container framework is Docker [41]. It unarguably started the container movement. Docker is open source system that provides an automated way to deplot applications inside containers [40].

Docker consists of multiple core components, described quite aptly by [41]:

- **Docker client and daemon:** the client is basically a command-line binary which performs requests for the daemon. The daemon itself can either be run remotely or on the same host.

- **Docker images:** labelled as the "source code "for the containers, images are the building blocks of Docker.
- **Registries:** used to store the images built. There are two types of registeries, public and private
- **Docker container:** applications and services are packaged inside containers. They are released from images and may contain one or more services.

Container performance is an important attribute to evaluate the quality of offered service. It represents system throughput, responsiveness, resource utilization, response time, latency, failure rate and fault tolerance [43]. With containers being very flexible and having the ability to fine tune specific metrics, the important question to ask is whether they can help preserve energy in certain scenarios. This will be further discussed in a later section.

Another technology that is quite interesting is edge based IoT middleware frameworks. One good example of is the Apache Cordova [44]. A typical IoT middleware comprises of a three-layer architecture i.e. edge, gateway and cloud [45]. A middleware is generally designed to be the intermediary between IoT devices and applications. The interaction is performed with the help of an *accessor*. Accessors provide the abstraction for smart things across different hardware or software platforms to interact. They further allow for smarter interactions, sharing and portability. They are usually implemented in Javascript to keep it lightweight and ubiquitous, allowing things to communicate to share information in a message oriented fashion [4]. An accessor has inputs, by which the swarmlet makes requests, and outputs, by which the service issues responses. The responses can be asynchronous and an accessor does not need to have an input; it can spontaneouly produce outputs [3]. This is also depicted in Figure 5. Accessor hosts function as a middleware service which is used to instantiate and execute accessors. They have

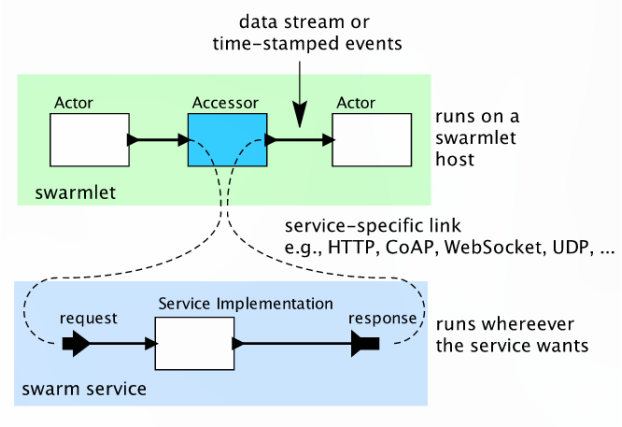

Figure 5: Design pattern of accessors [3]

their own specific set of actions that they can perform but the most common accessor hosts include Browser, Node and Cordova. The first supports executing accessors in a web browser whereas a Node host is just and Node.js engine with support for common host's capabilities [4]. A Cordova host is an extension of the Apache Cordova's cross mobile program development platform. It is used for building application using basic web development elements such as HTML, CSS and JS, in a unified code base and targeted to multiple platforms like Android and IOS. Other than writing the plugin for the respective target device, no additional programming is required as its javascript interface interacts with native language APIs of physical or virtual IoT devices.

The architecture of Cordova Accessor Host is given by Figure 6. Briefly, it consists of a webview and a Cordova Plugin. Webview comprises of an implementation for the Common Host, an implementation for accessor host specific to Cordova and a bundle of all community developmed accessors that can be shared. This is what makes up the Cordova Accessor Host. The swarmlet.js component acts as an entry method, used to launch the accessor pipeline.

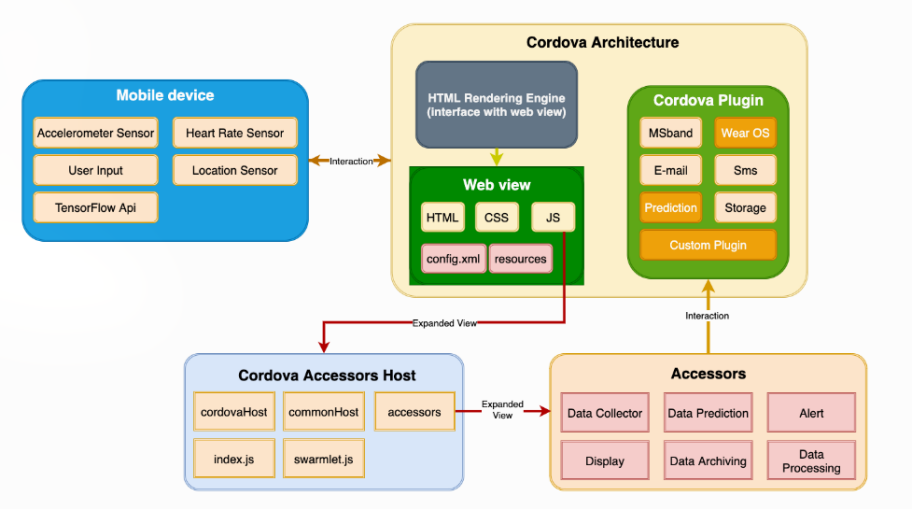

Figure 6: Design pattern of accessors [4]

III. Related Work

IV. Methodology

V. Evaluation

VI. Case Study

VII. Conclusion

APPENDIX SECTION

APPENDIX A

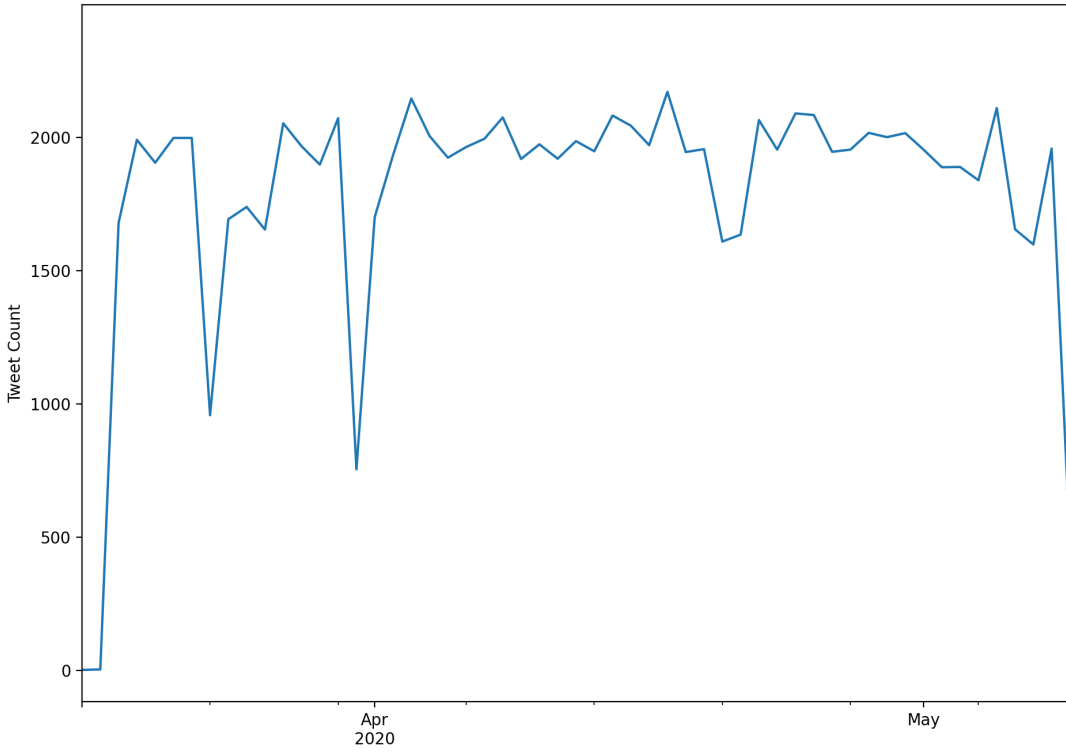

Figure A.1: First figure of appendix A. Captions of figures and tables in the Appendix section should not show up in the table of contents.

Table A.1: First table of appendix A. Captions of figures and tables in the Appendix section should not show up in the table of contents.

Dataset name	Number of records	Number of users
Dataset A	248	20
Dataset B	464	28
Dataset C	348	7
Dataset D	419	5
Dataset E	854	15

Table A.2: Second table of appendix A. Captions of figures and tables in the Appendix section should not show up in the table of contents.

Dataset name	Number of records	Number of users
Dataset F	1000	10
Dataset G	2000	20
Dataset H	3000	30
Dataset I	4000	40
Dataset J	5000	50

APPENDIX B

Table B.1: First table of appendix B. Captions of figures and tables in the Appendix section should not show up in the table of contents.

Column 1	Column 2	Column 3
1	2	10000
3	4	20000
5	6	30000

Table B.2: Second figure of appendix B. Captions of figures and tables in the Appendix section should not show up in the table of contents.

Column 1	Column 2	Column 3
A	B	10000
C	D	20000
E	F	30000

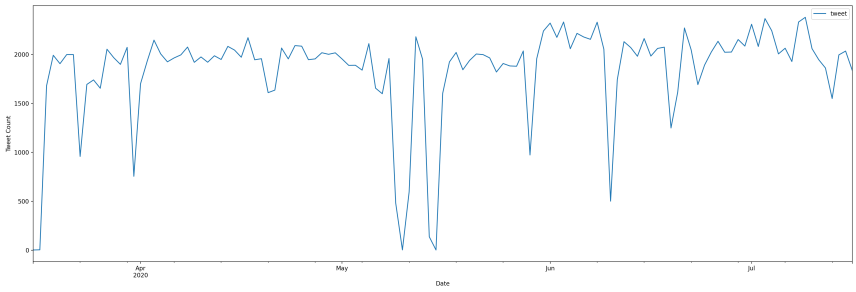

Figure B.1: First figure of appendix B. Captions of figures and tables in the Appendix section should not show up in the table of contents.

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