A Study of State-of-the-art Energy Saving on Edges

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ABSTRACT

Edge computing or Internet of Things (IoT) comprises a set of devices that are interconnected ranging from our daily used objects to advanced networked equipment. It is constantly evolving as the number of devices owned by users is increasing at a rapid speed. These devices are used for various scenarios such as health care, monitoring, autonomous vehicles etc. However, as the edges perform more complex operations and IoTs carry increasing heavy workloads, they demand more energy to perform such tasks. In this paper, we perform a comprehensive study of state-of-the-art energy saving on edge platforms. Specifically, energy efficiency of the devices that run on the edges as well as corresponding solutions including hardware, software, algorithms, etc. will be thoroughly analyzed and we also presented the strengths and weakness of various researches in each area.

CCS CONCEPTS

• **Computer systems organization** → *Energy consumption control*; **Edge computing**; • **Networks** → Network reliability.

KEYWORDS

IoT Devices, Edge Computing, Energy Saving

ACM Reference Format:
Kousalya Banka, Kun Suo, Yong Shi, and Sabur Baidya. 2021. A Study of State-of-the-art Energy Saving on Edges. In *2021 ACM Southeast Conference (ACMSE 2021), April 15–17, 2021, Virtual Event, USA*. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3409334.3452079

1 INTRODUCTION

Cloud computing technology is the third wave of innovation after personal computers and the Internet in past decade. It fundamentally changes the ways of using computing resources. The large amount of storage and computing resources integrated by cloud service providers can form economies of scale, and users can purchase corresponding services as needed at any time. The benefits of cloud computing are obvious, but with its growing scale and explosive growth of data, the energy consumption of cloud computing itself cannot be ignored. With the in-depth development of 5G, artificial intelligence, big data, Internet of Things (IoT), and mobile Internet, the power consumption of data centers will continue increasing rapidly, posing significant challenges to resources and the environment. In general, traditional cloud computing has three major shortcomings in energy consumption:

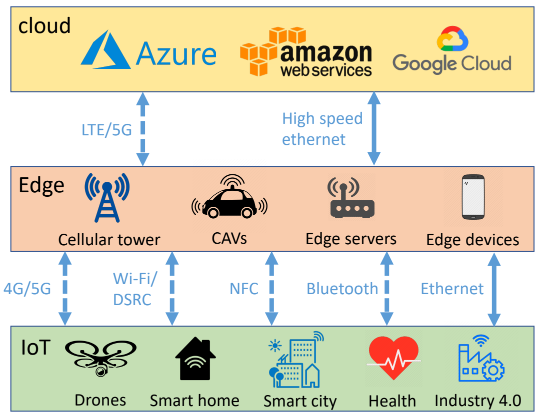

Figure 1: The Architecture of Cloud Edge Systems

First, cloud computing systems require a large number of hardware equipment to store and process data. Therefore, it inevitably consume huge overall energy. Second, resource utilization in the cloud is normally low. Many systems run in the cloud but actually do not provide services for users, such as services at night. Third, different from energy consumption units in traditional industries, the data center is spinning 24×7 and such round-the-clock operation is bound to increase energy consumption. Meanwhile, due to different requirements, cloud architecture varies dramatically. New and old machines, general and heterogeneous architectures are mixed, which further increases the difficulty of optimizing cloud energy consumption.

In order to address the above problems, edge computing which is designed for processing and operating the massive data generated by edges was proposed in recent years, as shown in Figure 1. Edge computing is a new type of computing model that performs most computing specifically at the edges. Over time, cloud will be

ACMSE 2021, April 15–17, 2021, Virtual Event, USA

ACM ISBN 978-1-4503-8068-3/21/04…$15.00
https://doi.org/10.1145/3409334.3452079

primarily used for storage and running complicated computational models, while most of the processing of data and AI inference will take place at the edge. AlefEdge [12] predicted that edge-computing market will reach at more than 4 trillion by 2030. Similar as the cloud, energy consumption of edge platform is also an important issue in current edge computing research, which significantly affects its design, application and development.

In this paper, we studied the energy efficiency in edges or IoT devices inspecting various aspects around the technology surrounded by them. We surveyed the most recent works in the aspects of hardware, software, offloading techniques and wireless network algorithms for edge energy savings as shown in Figure 2. We focused on how these factors have influenced the energy efficiency and the quality-of-service (QoS) and extend the lifetime of the limited battery resources. Specifically, we discussed the hardware energy saving techniques involving the CPU-GPU with various dynamic frequency and voltage scaling (DVFS) techniques for entire System on Chips (SoCs), memory usage with profiling, and smart use of advanced sensors. For software solutions, we studied latest solutions such as Cinder, CondOS, and Koala, which targets the energy optimization at operating system level. Next, task scheduling algorithms which are implemented in real-time IoT applications, and smart city [8] with Green IoT envisions, etc. have been covered as well. Edge computing also enables offloading tasks and this idea has been applied widely in IoT devices with the help of mobile cloud computing (MCC), content caching, etc. In offloading section we have also covered the solutions for complexity problems in urban areas. Furthermore, heterogeneous networks such as 5G with complex dense network architectures and its energy efficiency techniques without compromising the quality of the networks is discussed as well. For wireless networks solutions, we discussed about green cellular networking and D2D techniques to reduce the energy usage in base stations.

The rest of the paper is organized as follows. Section 2 briefly describes the energy efficiency techniques in hardware modules such as sensors, CPU, memory, and network. Section 3 studied the software solutions for energy optimization in operating systems, scheduling, and applications. Section 4 reviews offloading techniques and Section 5 investigates the wireless networks energy efficiency in 5G networks. Finally, Section 6 summarizes this paper with insights and conclusion.

2 HARDWARE MODULES FOR EDGE ENERGY OPTIMIZATION

Several research have tried to devise different methodologies to reduce energy losses. The hardware energy savings consist of CPU, memory, storage, sensors, and network, etc. All the functions of a hardware architecture work with the help of a battery that uses the various levels of the battery.

2.1 Energy Management for Entire SoCs

High performance at edges required in advanced processing ability hardware. However, small processing nodes at high temperatures can lead to higher leakage power. In modern PCs, the overall system power can be controlled by minimizing specific hardware energy utilization. Instead, most of the edge devices use integrated silicons such as M1 chips in latest Apple devices. Therefore, it becomes increasing important to control the energy consumption as a whole for edge or IoT devices. Currently, one of the most widely adopted techniques for dynamic power management in processors is the DVFS. Yang et al. [28] proposed one CPU DVFS technique to find the lowest CPU frequency for processor power efficiency. Nevertheless, the authors do not focus on thermal management for the entire hardware chips. The CPU and GPU are close to multiprocessor system-on-chip (MPSoC). Therefore, a slight change in the temperature can increase the temperature of the other components, this effect is called a thermal coupling effect. To control both the energy consumption and thermal balance, Prakash et al. [18] proposed a control-theoretic dynamic thermal approach for thermal management, which reduced both energy consumption and hot spot temperature of the MPSoC chip. Another trend of hardware energy control at edges is utilizing dynamic analysis and machine learning to address kaleidoscopic scenarios. Pathania et al. [16] proposed a power-performance model using linear regression to study the complex dynamics under different workload conditions in heterogeneous MPSoCs. They performed DVFS to control dynamic power based on previous observations and to stable the performance by achieving targeted frames per second (FPS) for CPUs in HMPSoCs for different gaming workloads. Tian et al. [23] combined reinforcement learning and DVFS techniques to optimize energy consumption among multiple mobile devices. Specifically, they proposed an optimized multi-device decentralized collaborative learning which evaluates multiple power settings in a dynamic run-time environment and converts into an appropriate configuration policy.

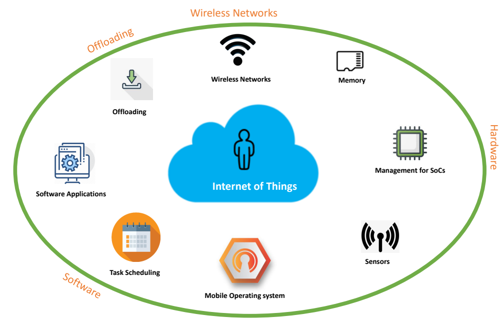

Figure 2: Categories of Energy-Efficiency in IoT

2.2 Smart Use of Sensors

As smartphones are becoming more powerful and a various range of built-in sensors in mobile devices are more accessed, the usage of applications providing sensor-based services, such as location services, have been increasingly popular. Moreover, with the growth of wireless interfaces and smart scenarios (i.e., healthcare, smart home, etc.), the use of sensor-based applications also increased. Unfortunately, these applications would consume large amount of battery of mobile devices. To minimize energy consumption, several schemes have been proposed for energy-efficient sensing, which combines different sensors usage history and probabilistic user behavior. probabilistic models of user location and sensor errors provide location-sensing and energy. Yi et al. [30] introduced an energy management framework for GPS sensing. These models work on Bayesian systems estimation to catch and build user's location and choose an application's accuracy necessities dynamically. Paek et al. [15] designed a system named RAPS (Rate Adaptive Positioning System) which makes it easier to know when to turn the GPS on and off. It uses Bluetooth to enhance accuracy and coordinate GPS readings along with neighboring mobile devices in GPS unavailable areas. The solution takes advantage of GSM cell tower information and reduce GPS activation to save more energy. By combining all these features, results indicated that power consumption was reduced to 40% compared to the approach where GPS is always on.

2.3 Use Memory Accurately

Many high power systems and data-driven applications execute memory intensive program and expend tons of energy in execution. For instance, mobile games require high memory throughput because of its complicated graphics and high frame rates. Modern computer systems are built with multiprocessors and use deep memory hierarchies to attain better performance. To identify and fix memory bottlenecks as well as corresponding energy consumption, many researches proposed prototype tools to analyze memory behavior of edge applications. Ailamaki et al. [1] studied database system performance and worked on the behavior of processors and memory interactions. For applications as in web servers, scientific algorithms, data warehouses, and data analytics, 50-80% of CPU cycles are consumed on delaying, resulted in a last-level cache (LLC) misses. Memory profiling approaches help the mobile application developers to define the memory behavior of the program. Dey et al. [9] introduced EMProf, a brand-new strategy to profile memory and the performance impact. EMProf can spot within the side-channels signal every LLC miss that stalls processor and exactly measure the period of that stall, especially in IoT and hand-held devices.

3 SOFTWARE SOLUTIONS FOR EDGE ENERGY OPTIMIZATION

3.1 Customized OS for Energy Optimization

In mobile or IoT devices, increasing computational power with various features like geo-tracking and advanced graphical user interfaces has led to the demand in controlling the energy allocation for the edge operating systems. Since inception of the energy efficient operating system proposed in 90s, multiple prototypes such as Odyssey, Ecosystem and Quanto were developed. In recent years, Roy et al. [19] designed Cinder, an mobile OS based on ECOSystem and Quanto, to better understand and control energy usage for energy-constrained devices by providing isolation, subdivision, and delegation to applications. Cinder uses two new abstraction taps and reserves along with resource consumption graph for energy allocation, where resource quality is defined by the reserves and the resources between the reserves are limited by the taps. Chu et al. [7] proposed CondOS, a context-aware operating system that manages the sensing resources at operating system level rather than application level. CondOS converts raw sensor data to contextual data units which can be queried by application and operating systems. This approach is also beneficial for effective memory management and scheduling on mobile platforms. Snowdown et al. [22] proposed Koala, a proactive way of allocating the resources based on the energy consumption and performance predictions by collecting individual statistics of the software running. Koala is built on Linux and supports various mobile platforms. During its execution, its behavior is checked with the system policy at each scheduling event based on this optimal conditions for the event are determined.

3.2 Scheduling

Mobile edge computing (MEC) improves the computation capabilities for mobile devices, in which offloading tasks to the server is the key to task scheduling in order to reduce the overhead on the edge resources. Chen [5] developed a decentralized computation solution for the multi-player gaming system which reduces the controlling overhead on the cloud. Nevertheless, this approach does not achieve high energy efficiency as they rely heavily on the processing capabilities of cloud CPUs, which are non-adjustable at mobile devices. Deng et al. [8] proposed a task scheduling algorithmic approach for the Internet of Vehicles (IoV) applications in a smart city. The initiator cognitive radio router enabled vehicles (CRV) to send parameters for distributed improved jacobi – alternating direction method of multipliers algorithm, and it transfers the respective tasks to correct CRVs through cognitive radio routers deployed. For the IoT devices, fog computing well-defined as a distributed computing that extends cloud computing applications to the "edge" of the network. Ma et al. [13] proposed IoT based fog computing model (IoT-FCM) by combining IoT and fog computing techniques. In this model, the optimized genetic algorithm is used to control three parameters (delay, energy, and distance) of nodes. Experimental results showed that the IoT-FCM algorithm was able to save energy an average of 150 KWH compares with other algorithms.

IoT devices run time-sensitive application, which demands high energy consumption due to computational intensity. Task scheduling is in focus for applications on multi-server mobile edge computing like real-time vision processing, where results are expected in seconds by reducing the total execution time while considering the task dependencies. Pendhakar et al. [17] presented the ant colony optimization (ACO), an approach used by ants to find the best possible way for the food. Through this design, the author tried to solve the constraint task allocation problem by utilizing the mixed integer programming and linear programming, where the results have proven to be helpful. Genetic algorithms (GA) are evolving algorithms where they eliminate inefficient solutions for task allocation by recommending only better solutions. Considering the individual benefits of GA and ACO approaches, Basu et al. [3] proposed a hybrid GAACO intelligent/cognitive task scheduling algorithm. This approach is used to derive the best task scheduling solution for IoT platform in a heterogeneous cloud environment. In this approach, ACO identifies the optimum path for the task scheduling and GA refines the path further. The experiments has proved it can achieve the energy efficiency with the reduced makespan.

3.3 Software Applications

Green IoT envision is designed to make the environment safe and helping the IoT devices reduce energy consumption as mentioned before that it is comprised of various heterogeneous applications. The entire service overhead increases with more devices deployed. IoT devices run predominantly on cloud platforms so it is important to effectively manage and allocate cloud resources. Al-Azez et al. [2] proposed mixed integer linear programming (MILP) where virtualized mini clouds are present in IoT network elements. Optimized clouds and the placement of the virtual machines reduces the traffic and processing which in turn reduces the power consumption. The cloud orchestration technique proposed by Sathyamoorthi et al. [21] predicts the behaviors of smartphones in reference to the context, location, and time. A cloud-based monitoring service would observe the power consumption with the help of data log collected from a large number of users. However, this research raises concern on the privacy and security of data.

In the user application level, researchers have proposed techniques in recent years to identify the energy usage patterns which can help developers to detect where the energy is consumed within their applications and optimize corresponding energy efficiency. For instance, battery-powered devices are not practical to run computation intensive tasks such as computer vision applications that execute deep CNN and demand high energy consumption. Reducing the model size for CNN by weight pruning is an option explored frequently. Han et al. [10] have applied sensitive weight reduction and formed a sparse iterative network. It can remove the unwanted connections, retrain to compensate for the connections removed and finally process to fine-tune the network. Whereas energy consumption is not solely dependent on the reduction of the number of weights, so the above researches were not able to effectively reduce the overall energy consumption. Yang et al. [29] tried to address the energy efficiency problem with a layer-by-layer pruning approach that reduces the number of non-zero weights by limiting the changes in feature maps instead of changes in filters. The algorithm cuts down the layers that have more energy consumption instead of the number of weights and the process continues till the lowest energy consumption layer.

4 OFFLOADING

In the past decade, cloud computing and wireless network communication technologies have expanded exponentially, which has caused a phenomenal increase in the edge and IoT devices development and deployment built on top of them. The user equipment today runs much more complicated applications like virtual reality (VR), augment reality (AR) and automatic driving than before. Even though the edge processing speed and ability are improved significantly, it is still critical to offload computation intensive and energy heavy workload to the server side. Chen et al. [6] designed a distributed computation algorithm to offload tasks to cloudlet based on the best resources available for the user, which reduces both energy consumption and network overhead. However, this approach does not consider the users leaving dynamically during the offload period and predominantly works on single mobile edge computing server. Chen et al. [4] divided the optimization into sub-problems, using the software-defined network for resource allocation and task placement. Though proposed offload scheme, it can achieve 30% energy saving and 20% in task duration compared with other offload schemes.

In the urban areas, ultra-dense networks create a complex environment with thousands of devices. To reduce the complexity in decentralized solutions, task offloading and service caching should be coordinated with all base stations. Barbarossa et al. [20] considered optimizing the radio and computational resources together to achieve energy efficiency using an iterative algorithm for MEC within energy and latency constraints. However, these researches do not consider 5G wireless networks and are less effective in the modern ultra-dense network scenario. Zhang et al. [32] designed the offloading framework for MEC in heterogeneous 5G networks referred to as energy-efficient computation offloading (EECO), which optimizes the assigned radio resources and offloading computation decisions by considering latency constraints.

Content caching and computation offloading are key in dealing with exponential growth in internet traffic. IoT devices are heavily reliant on offloading large number of tasks to edge servers. Therefore, in-network caching has been effective to handle the huge load on the network. Wang et al. [24] improved the research by defining the caching strategies to increase the caching revenue and applying various spectrum amounts and computation resources to UEs. However, it is observed that the latest virtualization concept in wireless networks could bring in more added value. Wei et al. [25] studied the edge server shareable cache that stores the computation results and incoming data. Author proposed cache-aware computation offloading location to resolve the transportation problem. To achieve the energy efficiency, based on the estimated execution time, online execution time estimation will determine the best offloading location and reduce the latency. Zahed et al. [31] addressed the security challenges that the caching of the tasks into MEC server as they are exposed to multiple users and prone to attacks. The authors proposed the resource-constrained optimization model to reduce the energy consumption while securing the network information.

5 WIRELESS NETWORKS

With the spread of edge or IoT devices, wireless networks have become essential for our daily life and produced enormous amounts of data thus incurring escalation of energy demand. IoT devices such as wireless sensors, drones, smart meters, and mobile phones are heavily dependent on wireless networks to provide timely information. Wu et al. [26] discussed green cellular networking where the high energy-consuming base stations of cellular networking are turned into sleep mode when their network load is low. However, this idea increases the burden on the user equipment as it increases the transmission distance and consumes more energy for the user equipment. A better trade-off strategy is required to balance the green solutions for mobile equipment and cellular networks. Ismail et al. [11] consolidated the studies on the base station and mobile terminals by considering the power consumption, traffic models and throughput for mobile users and cellular network base stations, and proposed a trade-off to find the balance for the IoT devices and network providers.

Recently, almost every major network carrier has launched its 5G wireless network. The primary focus will be on standardizing the efforts to increase energy efficiency and reduce the carbon footprint. Massive multiple-input multiple-output (MIMO) is an approach which can help increase energy efficiency in wireless networks. It is the process of employing a large number (hundreds or more) of low-powered antennas which are smaller in size than regular, downsizing the signal power radiation and bringing the IoT devices and base stations closer for better throughput. The results show that the energy efficiency is proportional to the square root of deployed antennas [14]. Whereas the cost of this deployment is huge as it suggests this implementation would require a massive number of low-power BS. Another solution named visible light communications (VLC) [27] is used for short-range wireless communications. Compared to the traditional ways, it provides greater energy efficiency and larger bandwidth capacity to support increased data-rates. However, although this approach is considered very inexpensive, it still has limitation on the range of network it can operate.

6 CONCLUSION

Edge and IoT devices have become an integral part of many industries. As they introduce more functionalities to support ever increasing customer needs, their computing power increases exponentially and energy efficiency for these devices has become an essential performance measure. As shown in this survey, there are many ways the energy efficiency can be achieved from the IoT devices hardware, software to its supporting technology (offloading techniques, wireless networking, etc.) surrounding the edge computing techniques. We have summarized the advantages and the performance gains from theoretical and practical observations and discussed the possible challenges for each category in the present environment and future technological advancements. Whereas many policies, regulations, technical and business challenges still need to be addressed to achieve more energy efficiency, we hope that this research survey can guide the optimization of existing energy solutions and shed light on further exploration. In future research, we are going to investigate for security and privacy in IoT energy efficiency solutions with all devices sharing a lot of data and resources.

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