Energy Efficiency on Edge Computing: Challenges and Vision

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***Abstract*—The Internet of Things (IoT) has been the key to many advancements in next-generation technologies for the past few years. With a conceptual grouping of ecosystem elements such as sensors, actuators, and smart objects connected together, complex operations like environmental monitoring, intelligent transport systems, smart buildings, and smart cities are able to be performed. Edge computing technology extends the reach/scope of IoT ecosystems, offering robust and powerful computational capabilities by connecting multiple devices through the Internet. Unfortunately, this form of computation comes with a significant drawback with strict energy constraints and low power efficiency, which highly limits its potential and usage. In this paper, we present some of the challenges in the planning of energy-efficient IoT edge devices and discuss some of the recent research efforts that proposed promising solutions that address these challenges. Specifically, we first analyze the challenges and reasons for improving the energy consumption of edge platforms and IoT devices. Next, we perform case studies that outline the energy-saving techniques in smart grids, smart cities, electric vehicles (EV), smart home devices, and Virtual Reality and Augmented Reality (VR/AR). We further discuss different approaches such as computation offloading, edge devices hardware and software designs, and a number of algorithms that help reduce energy consumption. Finally, we outline possible future directions and our vision of improving energy efficiency on edge platforms.**

***Index Terms*—Energy Saving, Power Efficiency, Edge Computing, Internet of Things, Smart System**

I. Introduction

Traditional cloud computing is becoming increasing insufficient to support the emerging applications and services such as 5G network, IoT and embedded Artificial Intelligence (AI). In recent years, edge computing [1] is proliferating in usage and popularity with large amounts of edge devices such as Electric Vehicles (EV) or smartphones in our daily lives. For instance, recent surveys [2], [3] revealed that the number of EVs worldwide in 2020 reached 6.8 million and the number of mobile devices in 2020 was 14 billion. By integrating local computing, storage, networking, and resource management with applications, edge computing can effectively meet the latest requirements, including real-time analytics, local control, constrained network bandwidth, data security, etc.

Despite the benefits, there exist many unique challenges for energy control and power efficiency in edge computing compared to traditional cloud computing. First, the number of existing edge devices is immense and rapidly expanding. With new technologies, such as 5G deployment, the location and number of edge servers are essential. Ideally, the number of edge servers should be maximized to minimize the delay of requests and handle spikes in network traffic, which often introduce substantial energy usage and cost. Although the energy usage of a single edge node is insignificant, the overall consumption could be significant due to the scale of the edge servers and nodes. Second, the utilization of edges is usually low, but the energy consumption of edge servers or nodes is non-negligible. For instance, the IoTs deployed to control traffic lights are busy in the day while idle at night, resulting in energy waste [4]. Additionally, the demand for computing resources is inconsistently distributed across the areas. Considering that deploying edge servers typically cannot catch up with the changes of distribution in computing resource requirements, efforts should focus on server placement and optimization of instrument utilization intelligently to reduce energy usage. Lastly, edge devices are more diverse and complex in comparison to traditional cloud computing. The runtime environment and data on each device are different and fragmented, making it difficult to control the energy consumption in edge scenarios. For instance, EVs and smart buildings are complicated edge nodes that consume lots of energy, while wearable devices and smart lights are simple and their energy control policies could be easily deployed. As various edge devices have their scenarios and structures, flexible policy integrated with hardware and software should be applied for energy efficiency.

To address the above challenges, there currently exist several surveys analyzing edge computing and its energy efficiency. Specifically, Khan *et al.* [5] performs a study discussing the state-of-the-art in edge computing paradigm. Similarly, Abbas *et al.* [6] performs a survey on mobile edge computing (MEC) covering the entirety of edge computing and discuss topics such as MEC advantages, architectures, and application areas. Different from the above, this paper specifically focuses on energy efficiency on edge computing, discussing topics including current inefficiencies, case studies, and possible efficient solutions. Similarly, other researchers like Jiang *et al.* [7] have investigated energy-aware edge computing and provided a systematic review on energy efficiency of edge devices and edge servers. In comparison, the contribution of this research provides a method for analyzing current inefficiencies and an in-depth study of modern edge applications, and vision of future directions in edge energy efficiency.

The rest of this paper is organized as follows. Section II discusses with background information on edge computing and the current limitations in energy saving on edges. Section III performs case studies on energy efficiency of various edge scenarios and Section IV presents in-depth discussions on energy efficiency methods. Section V discusses future directions and our vision of energy efficiency on edge computing, and Section VI concludes this paper.

II. Background

A. Edge Computing

Edge computing provides computing, storage, and network resources at the location where the data is produced. The traditional cloud has extensive computing power and storage capacity and can support millions of applications and services. However, due to resource constraints at the edge, cloud services will inevitably be affected by high latency, bandwidth issues, and network instability. By migrating some or all of the processing to the edge, the impact on applications under the cloud architecture and stress on networks can be reduced significantly. For example, the Boeing 787 [8] produces terabytes of sensor data each flight. If all of this data is uploaded to the cloud, the latency and network inefficiencies can impact decision-making and data processing. Conversely, by deploying the computing on the edge, feedback can be given in real-time. As most of the useless data can be filtered, edge computing can effectively reduce the workload while reducing resource consumption and protecting data privacy.

B. Energy Inefficiencies in Edge Computing

In recent years, there has been a significant increase in the solutions to decentralize computing, communications, data collection, and processing by moving from the cloud to the edge. Therefore, power consumption and energy efficiency become crucial factors for developing and deploying modern edge computing. However, we found that there lacks a comprehensive study of energy efficiencies on edge platforms. In this section, we survey existing energy optimization and power efficiency efforts and summarize three aspects of energy inefficiency in edge infrastructures: communicating with the cloud, hardware, and software.

Cloud Communication Inefficiency. While edge computing is becoming increasingly powerful these years, certain computations or tasks, such as Siri on iPhone or Alexa on Amazon echo, are still needed to compute onto the cloud. As a result, the transmission of data, as well as computation between the edge and cloud, generates additional energy consumption and inefficiencies. The first challenge faced by edge computing is the task scheduling of the computation offloading. Due to the geographical distribution of cloudlets, which are small-scale cloud data centers located at the edge of the internet, there exist difficulties when cloudlets need load balancing while lacking centralized control. Second, due to the variety of tasks performed by the edges and complex network connection, including 3G, 4G, 5G, dedicated short-range communication (DSRC), as shown in Figure 1, delivering the same Quality-of-Service while controlling energy cost becomes difficult. As edge computing is distributed and interactive, trust domains have been necessary for safe operation. To ensure security and privacy, edge devices usually adopt encryption technology to secure data before transmission. The necessary

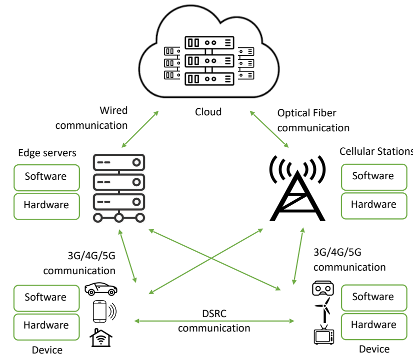

Fig. 1. The architecture of cloud edge systems

security requirement will also introduce additional computation and energy consumption to the edge platforms [9].

Hardware & Software Inefficiency. There exist many gaps across the edge hardware and software stack. Many edge devices, such as mobile phones, wearable devices, and EVs, heavily rely on battery power. According to Moore's Law, the number of on-chip transistors doubles every eighteen months while it might take ten years for battery manufacturers to achieve similar growth. The traditional power optimization on the cloud can also not be simply copied to edge computing or IoT devices. The workloads on the cloud are usually computation-intensive or I/O-intensive. Impertinent migration from cloud to edge devices will widen the gap between the service requirement and the insufficiency of edge resources. The design principles and services of most modern applications usually emphasize performance while ignoring energy efficiency, especially for edge platforms. Despite numerous types of hardware, there exist various software and configurations in computing, storage, and network settings at the edge. Cong *et al.* [10] found that standardized communication protocols support many unnecessary functions of edge applications, resulting in redundant power usage while transmitting useless data required by HTTP transactions. Different capabilities in wireless signals, sensors, computing, storage, etc., incur non-negligible overhead and operation complexity, which results in significant power usage on edge platforms.

III. Case Studies of Edge Energy Efficiency

Edge computing has been widely used in many scenarios. This section aims at five typical applications of edge computing, analyzes the control and challenges of energy consumption, and discusses future possibilities and directions.

A. Smart Grid

Smart grids are a vision of a traditional power grid integrating green and renewable technologies. The smart grid is an electricity network enabling a two-way flow of electricity and data with digital communications technology, enabling it to actively react to changes or issues [11]. Instead of a traditional power grid that uses one-way energy consumption, smart grids collect the user's electricity usage data for analysis and adjust

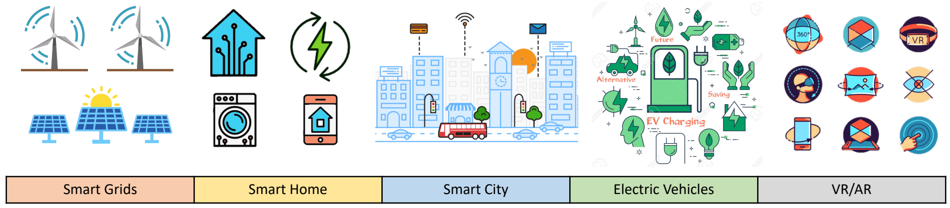

Fig. 2. Edge computing in smart grids, smart homes, smart city, electric vehicles and VR/AR

the energy plan for users based on the consumption reducing energy waste by querying energy usage in real-time. Smart grids can collect various signal quantities, such as voltage and current, for real-time updates improving infrastructure reliability, fault prediction, and rapid adjustments. The current state of smart grids is still not optimal due to energy waste and inefficiencies still prevalent. First, in terms of grid operations, most of the data is separated and real-time sharing is weak. Secondly, smart meter terminals collect overwhelming quantities of data, resulting in insufficient response times. Third, new scenarios appear and become more complex, which require more accurate and localized data processing to achieve customized and intelligent management.

B. Smart Home

Smart homes can provide highly efficient human-computer interaction, safe control, and configurable efficient functions. Many smart home solutions exist currently such as the Amazon Alexa, Apple HomeKit, and Google Home, that provide users with a rich user experience and functions. The energy consumption of a smart home grows with the number of devices connected. Future Tech Lab estimated 470 devices are connected in the upcoming smart home [12]. Three categories are the primary source of energy consumption in a smart home: the smart device itself, communication system, and control system. First, smart home devices are typically on standby 24 hours a day. For example, a smart speaker is always collecting surrounding audio signals in a working mode and power-consuming state. Second, smart devices are heterogeneous, meaning the data they produce is unique and has different exchange methods. Wired communication allows high data transmission speed and strong anti-interference ability, but the wiring is expensive and cumbersome. In contrast, wireless communication built on communication protocols such as Bluetooth or Wi-Fi allows dexterous configuration, automatic networking, and flexible management. However, wireless and wired communications still generate additional energy consumption during the execution. Lastly, most smart home devices are controlled by connected smartphones or home gateway control systems that consume additional energy.

C. Smart City

Smart cities combine urban areas with modern technology to collect data and utilize the data for optimizations in real-time and increase energy efficiency. Cities consume 70% of the world's resources and consume significant amounts of energy due to the population growth and economic and social activities in these urban areas [13]. Two aspects are the main contributors to energy consumption in smart cities. First, smart cities utilize cloud computing, edge computing, and the IoT to connect the infrastructure with numerous sensors, devices, and equipment smart cities require the energy consumption is going to be immense. Second, smart cities produce an extensive amount of heterogeneous and rich data, and collecting, processing, and communicating this data results in non-negligible energy consumption. To address the energy consumption, it is necessary to formulate efficient and intuitive standards for use in lighting, buildings, roads, etc. In the past, city infrastructure data was sent to the cloud for processing but with edge computing and embedded systems, the data processing and computations can be done in real-time at the edge and reduce energy consumption.

D. Electric Vehicle

The popularity of electric vehicles (EV) has soared over the years with the advancement of EV technology with the primary leaders such as Tesla. EVs use electric motors powered by rechargeable battery packs in comparison to combustion engines in traditional vehicles, EVs convert over 77% of electrical energy to power at the wheels while gasoline vehicles only convert around 20% of energy stored in gasoline [14]. The two main problems facing EVs are the short driving range and low battery energy density. The range of EVs is constantly increasing, but most have a limited range of 200-300 miles and charging can be a time-consuming task. Even with the quick charging feature, it takes 30 minutes to achieve 80% capacity [14]. Tesla has been developing their new batteries, most recently the 4680 battery that increases the energy density of a single cell by 5 and charging efficiency by 6 times [15]. Mullen Technologies, another EV manufacturer, proposed a solid-state polymer battery with the potential to increase the cruising range of EV to 1,000 kilometers [16]. In addition, many EVs employ energy recovery technology, such as regenerative braking, to convert kinetic energy into electric energy in the battery during deceleration.

E. VR/AR

Virtual reality (VR) provides a 360-degree immersive virtual world and allows users to interact with it. Augmented reality (AR) brings elements of the digital world into the real world, allowing users to conduct real-time 3D interactions. The algorithms built for VR and AR applications consume a significant amount of energy [17]. VR headsets also need to maintain a latency of fewer than 20 milliseconds to prevent users from becoming dizzy [18], and with the real-time computing and performance requirement for complex visuals, the energy consumption is high. To reduce energy consumption scientists, researchers, and companies have implemented chip, display, and software optimizations. Meta's Oculus Quest 2 uses the Qualcomm Snapdragon XR2 processor extending battery life by 2 to 3 hours and featuring a Video Analysis Engine dedicated for computer vision [19]. InifniLED, owned by Oculus VR, developed an Inorganic LED Display, a low-power energy-efficient display, for VR with a 40 times reduction in power consumption [20]. Meta's research department developed a graphics rendering system based on neural networks called DeepFovea that uses high-resolution fields of vision for areas where the vision is concentrated and pixel downgrades peripheral images [21].

IV. Energy Efficient Methods

In this section, we surveyed the state-of-the-art techniques and efforts to address the energy inefficiency of the above scenarios and categorized them into three groups: computation offloading, energy-saving designs in hardware, and energy-saving features in software.

A. Computation Offloading

Energy Efficient Offloading. Edge computing is constrained by the lack of powerful processing power due to its compact form, computation offloading can be employed to efficiently offload to the cloud or other edge servers or nodes to improve energy efficiency. Bi *et al.* [22] introduced an energy-optimized partial computation offloading for mobile-edge computing using a genetic simulated-annealing-based particle swarm optimization. Zhang *et al.* [23] proposed an energy-efficient computation offloading technique for 5G heterogeneous networks to optimize computation offloading allocation strategies and radio resource allocation. Huang *et al.* [24] introduced an energy-efficient offloading for mobile edge computing in vehicular networks using a Lyapunov-based dynamic task offloading decision algorithm.

Partial Offloading. Computations are not required to offload entirely, and partial offloading can be employed and is quickly becoming the most common offloading technique. Wang *et al.* [25] introduced a partial computation offloading technique in mobile edge computing using dynamic voltage scaling, by employing a latency-optimal partial computation offloading algorithm and an energy-optimal partial computation offloading algorithm they successfully minimized energy consumption and energy usage. Ning *et al.* [26] proposed a cooperative partial offloading solution for IoT devices, in which they designed an iterative heuristics mobile edge computing resource allocation algorithm that improves upon present schemes in the areas of latency and offloading efficiency. Saleem *et al.* [27] considered a device-to-device mobile edge computing offloading scenario where either devices or servers nearby can be used for offloading, by applying a joint partial offloading and resource allocation scheme they reduced latency and energy usage.

Intelligent Offloading. To further optimize offloading AI, machine learning (ML), and Deep Learning (DL) can be employed to strategically offload computations based on resource or network constraints. Yu *et al.* [28] developed a deep supervised learning method for mobile users in which network conditions, local overhead, and application are used to calculate the optimal offloading method reducing system cost by 15.69% in comparison to total offloading. Ning *et al.* [29] employed an intelligent offloading system for vehicular edge computing by dividing up the joint optimization problem into subproblems they can use a two-sided matching approach for scheduling offloading requests and a Double Deep Q-Network algorithm for the resource allocation. In smart cities, IoT, Xu *et al.* [30] presented an intelligent offloading method in which they develop an offloading algorithm using an ant colony optimization approach to minimize service response time, optimize energy consumption, and maintain load balancing.

B. Energy Saving Designs in Hardware

System on a Chip. System-on-a-Chip (SoC) designs are being adopted to reduce energy waste and inefficiencies in the hardware of edge devices. Apple began using the M1 chip and more recently the M1 Max and M1 Pro chips, a SoC to improve performance and energy efficiency that features a unified memory architecture and all computing components on one chip [31]. The M1 Pro and M1 Max can achieve 70% less power usage while being 1.7× faster than an 8-core Intel chip with the same power level [32]. ARM Holdings developed a SoC, big.LITTLE, that utilized a "big" processor for computation heavy workloads and a "little" processor for less intensive computing with energy efficiency in mind [33]. Qualcomm's latest mobile platform processor, the Snapdragon 888 5G, is based on the ARM Holdings Cortex-X1 [34] and uses Kyro 680 CPU, Adreno 680 GPU, and Hexagon 780 processor to achieve an efficient SoC [35].

Domain-specific Chip. Domain-Specific System-on-a-Chip (DSSoC) can increase the energy-efficiency of specific domain computation by orders of magnitude compared to the general processors. Qualcomm's APQ8096SG is a processor directed at IoT applications such as VR due to its small form, performance, and power efficiency [36]. Nvidia claims their mobile chip the Tegra X1 is their most advanced mobile processor with performance 13 times better than a 2015 Apple TV and features a 256 core GPU and 4-core 64-bit CPU [37]. Mobileye develops technology for self-driving and advanced driver-assistance vehicles and their latest processor is the EyeQ5 which supports fully autonomous vehicles. Can achieve performance efficiency due to proprietary computation cores, named accelerators, that are optimized for computer-vision, signal-processing, and machine-learning tasks [38].

Memory and Networking. 5G is the latest generation of mobile networks and is becoming heavily adopted into edge devices such as mobile phones. 5G allows higher network speeds, improved reliability, and less latency while consuming a fifth of energy for a single bit compared to 4G [39]. Wen *et al.* [40] proposed a hardware-accelerated memory manager with data placement data migration policies for use in future mobile hybrid systems achieving a 39% reduction in energy usage and only a 12% loss in performance. Samsung developed the next-generation mobile device RAM, LPDDR4X, with 17% less power usage, 15% performance increase, and up to 12GB of storage in a compact form. In addition, a new generation of Bluetooth chips (e.g., Nordic nRF52811) and ultra-wideband chips (e.g., Apple U1) can also bring low power consumption, high bandwidth, and simple communication to wireless interfaces and personal LAN access.

C. Energy Saving Features in Software

Operating Systems. Operating systems can restrict powerful and efficient hardware if it is not optimized. Specifically, Apple's iOS and Android have been optimized over the years to properly utilize the efficient hardware and software. Apple can achieve efficient hardware-software integration in their devices and push developers to create efficient applications on the app store due to creating a homogenous ecosystem [41]. Android and iOS both contain a low power mode feature that allows users to limit battery drain by limiting certain features such as cellular data usage and throttling performance. iOS utilizes several energy-saving technologies including intelligent app management, network operation deferral, task prioritization, and developer tools. Intelligent app management allows the system to place apps that are not being interacted with by placing them into a background state, similarly, task prioritization prioritizes tasks that affect the user over background tasks. Network operation deferral allows developers to designate a network operation deferral through APIs and the system then defers the network operation until an energy-efficient time. Lastly, Apple has developer tools in Xcode to help application developers find and fix energy-inefficient problems before they affect users [41].

Algorithms. Algorithms can be utilized alongside operating systems to reduce potential energy offloading transmissions or performing computations. Li *et al.* [42] proposed a particle swarm optimization energy-aware edge server placement algorithm that can reduce more than 10% energy consumption and over 15% improvement in computing resource allocation compared to other algorithms. Zhu *et al.* [43] presented a task-scheduling framework reducing the number of task-switching times and active tasks resulting in efficiency over 98% in most cases. Xu *et al.* [44] proposed an adaptive differential evolution algorithm for energy control frameworks to calculate the optimal load pattern and corresponding energy storage capacity of battery energy storage systems.

V. Vision & Future Directions

The high energy consumption of edge computing not only causes waste of power and unstable system operation but also harms the environment and social security. The energy consumption management of edge computing platforms is still in its early stage, and there are still many problems that need to be further studied. In this section, based on the analysis and summary of existing technologies, we propose several future directions worthy of further research.

Virtualization on Edges. The rapid development of virtualization technology provides new solutions to the energy management of edge computing. Virtualization has advantages in resource consolidation, online migration, isolation, high availability, flexible deployment, and scalable management. For example, through virtualization, multiple workloads are integrated on the same node through consolidation, and idle physical edge nodes could be shut down to achieve energy saving. In recent years, lightweight virtualization such as containers [45], [46] and serverless systems can further realize fine-grained resource management, dynamic migration, and load balancing to reduce power consumption.

Collaborative Energy Management. At present, the integration of energy consumption management at different layers, such as the hardware layer and the operating system layer, to achieve fine-grained energy consumption management, is receiving more attention. The energy-saving of multi-dimensional resources is also a hot research direction in recent years. Most of the current work only considers the energy saving of computing resources, and rarely involves other energy saving such as storage resources (including file systems) and network resources. Different system components and layers, such as processor, operating system, application layer, etc., provide their energy management strategies. Additionally, different manufacturers will also have their power control mechanisms. How to coordinate these energy management designs and solutions at different levels or from different sources to maximize energy-saving performance is an issue that needs to be resolved.

Accurate Measurement & Modeling. To achieve efficient energy management and control, it is important to implement richer energy consumption monitoring and measurement methods at the hardware and software layers and to provide raw data in a timely and accurate manner. For example, the energy consumption of various hardware is different. The energy consumption model of the CPU depends on multiple factors, such as the activity of the processor subunits and the execution of specific instructions. The study of the memory energy consumption model found that the main factor affecting its energy usage is the memory read and write throughput. In addition to the energy consumption model, we also need to establish a multi-factor driven and lightweight system to trace overall energy consumption that can predict energy hot spots, indicate trends and find a causal relationship.

Personalized Energy Saving. In an edge computing environment, workloads are diverse, and their resource and energy efficiency requirements are also different. Meanwhile, the software and hardware system runtime environments are also significantly disparate. How to use ML and AI technology to dynamically apply personalized energy-saving solutions based on existing conditions is also an interesting question.

VI. Conclusion

The potential of edge computing appears to be great as an evolving technology being applied to various new and existing industries. However, the energy consumption of edge computing has always hindered its advancement. In this paper, we introduced the energy efficiency of edge computing and discussed the current limitations in energy saving on edges. We presented case studies where we analyzed edge scenarios including smart grids, smart homes, smart cities, EV, and VR/AR. Existing efforts such as computation offloading, efficient software, and advanced hardware that is applied by the researchers are discussed based on thorough analysis. Based on the above, this paper proposes future directions worthy of further research from the four aspects of virtualization, collaborative energy management, precise measurement and modeling, and individualized energy saving. Since the energy consumption research of edge computing is still in the early stage, we hope this research could shed light on other researchers to make breakthroughs in this area.

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