Energy Optimization for Deep Learning in Edge Computing: An Overview

# INTRODUCTION

Edge computing

Deep learning

Energy concerns, optimization and challenges

# BACKGROUND

## Background on Edge computing

## Background on Deep Learning

# Industrial Applications (Energy-efficient DEEP LEARNING in Edge)

There are many existing studies on applying energy-efficient deep learning techniques in edge computing. They mainly focus on the following industrial applications.

## Internet of vehicles (6)

Vehicular edge computing (VEC) is the application of mobile edge computing (MEC) in vehicular scenarios, and it has received great attention.

Wang *et al.* [1] consider an increasingly prominent challenge of meeting communication and computational needs of vehicles with the emergence of vehicular applications. Fog computing improves the performance of vehicular services by using computational offloading at the network edge. They design a fog-cloud computational offloading method in Internet of Vehicles (IoVs) for minimizing both the power consumption of vehicles and that of computational facilities. An offloading problem is formulated as an NP-hard one, and solved by a heuristic algorithm gradually. Specifically, a predictive combination transmission mode is designed for vehicles, and a deep learning model is establishes for computational facilities for determining the optimal allocation of workload.

Ning *et al*. [75] consider the challenge of how to meet quality of experiences of users in intelligent networks with limited computing abilities of vehicular fog nodes. Fog computing infrastructure is deployed closely to terminals, and provides updated communication and computing platforms to emerging vehicular services. They develop a three-layer offloading framework for Internet of Vehicles (IoV) to minimize their total energy consumption while meeting delay constraints of users. Considering the high computational complexity, an optimization problem is formulated and decomposed into two parts including flow redirection and offloading decision. Then, a deep reinforcement learning-based mechanism is proposed to solve it. Real-world data-based evaluations show that the average energy consumption is reduced by 60% compared with the baseline algorithm.

Jiang *et al*. [19] consider a hybrid mobile edge computing (HMEC) platform including ground vehicles (GVs), ground stations (GSs) and unmanned aerial vehicle (UAVs). They are connected with mobile edge cloud that enables Internet of thing (IoT) devices or user equipments (UEs) to offload intensive computing tasks. It aims to develop an online offloading algorithm to achieve the energy consumption minimization for all UEs by optimizing positions of UAVs and GVs, user association and resource allocation in a dynamic environment. Then, a hybrid deep learning-based online offloading framework is designed and it applies a large-scale path-loss fuzzy c-means algorithm to predict the optimal positions of GVs and UAVs. A fuzzy membership matrix U-based particle swarm optimization algorithm is adopted to produce sample datasets for a deep neural network (DNN). Then, a DNN with a scheduling layer is developed to obtain computing resource allocation and user association while meeting practical latency needs of tasks with limited computing resources and energy of HMEC.

Lammie et al. [76] consider the challenging problem of the robust and efficient detection of weed species in robotic weed control technologies. Deep neural networks (DNNs) have demonstrated remarkable performance for plant classification. Training DNNs on graphics processing units (GPUs) provides higher levels of performance; however, GPUs consume large power. The field programmable gate array (FPGA)-based DNNs have many advantages in energy efficiency compared with traditional GPU- and CPU-accelerated networks. DNNs networks that are properly designed and customized on GPUs and FPGAs, are ideal candidates for inference and learning in resource-constrained and power-limited portable devices, e.g., robots and edge devices in Internet of Things (IoT). They adopt GPU- and FPGA-accelerated DNNs that are deterministically binarized for weed species classification in robotic weed control. Their results show that the FPGA-accelerated binarized networks dramatically outperform the GPU-accelerated ones in terms of power consumption reduction and weed image inference time. It provides a significant step for deep learning and inference on IoT edge devices, and portable machines like agricultural robots.

The fast increase of data processing needs from users in MEC, the traditional mobile edge servers (MESs) fail to provide effective and timely services. To solve it, Li *et al.* [37] tries to adopt unmanned aerial vehicle (UAV) as an MES that provides offloading of computational tasks for users. They aim to maximize the migration throughput for users’ tasks with UAV that only has limited energy. A maximization problem is formulated as a semi-Markov decision process without transition probability. Then, a deep reinforcement learning (DRL)-based scheme is proposed to maximize the migration throughput of user tasks. It achieves a maximum autonomic migration throughput for users’ tasks with limited UAV energy and improves quality of service of MEC.

Zhan *et al.* [81] consider a computation offloading scheduling problem in a VEC scenario, where a vehicular terminal (VT) travels along an expressway, and makes the scheduling decision for tasks waiting in their task queue. These tasks are independently produced by different applications, and therefore they have heterogeneous characteristics in terms of data size and computation-to-volume ratio. They lead to dynamical changes of data transmission time, energy consumption and transmission failures. Servers in MEC are equipped in roadside units (RSUs) are executed to perform computation for the VT. The resource-demanding tasks can be offloaded to MEC servers in RSUs for significantly reducing the energy consumption and execution latency of in-vehicle applications. They consider a key challenge of how to achieve a trade-off between energy consumption and task execution latency. To tackle it, a DRL-based offloading approach is designed to minimize the long-term cost in terms of a trade-off between task latency and energy consumption. Their DRL implementation is proposed according to a proximal policy optimization algorithm. It combines a parameter-shared network architecture with a convolutional neural network to approximate both value and policy functions for effective representative feature extraction.

## Microgrid (5)

Munir *et al.* [3] consider a problem of risk-sensitive microgrid energy profiling for a MEC network. It considers conditional value-at-risk and determines the predicted energy shortfall risk by using the coordination with uncertainties of both supply and demand. A multi-agent system is designed to specify an optimal scheduling strategy for the agents. Then, a multi-agent deep reinforcement learning based on asynchronous advantage actor-critic is adopted to mitigate the dimensionality curse and design the optimal energy profile among agents. Their results show that the proposed model realizes high-accuracy energy profiling than a single agent solution. Munir *et al.* [39] propose an energy supply plan for MEC networks supported by microgrid. An energy consumption minimization problem is formulated for microgrid-enabled MEC networks. It is a mixed integer nonlinear optimization one with tasks’ latency and computational constraints, and it also considers the uncertainty of both energy generation and consumption. It is decomposed into two subproblems including energy-efficient tasks allocation and energy supply plan. In addition, a density-based spatial application clustering is applied to solve the first one for each base station, and a model-based deep reinforcement learning is adopted to the second one. Naderializadeh and Hashemi [66] consider a computation offloading problem in a MEC architecture, and many energy-constrained users simultaneously offload their tasks to servers with a shared wireless medium. A multi-agent deep reinforcement learning method is proposed where an agent is designed for each server and it observes its associated users’ status and chooses the optimal offloaded user in each step. The task completion time and system lifetime are selected as two key performance factors, and their results prove that the proposed method achieves better performance than baseline algorithms. Khan *et al.* [95] introduce the factors that affect the selection of microgrids as major electrical grids, and gives benefits of microgrids. In addition, they consider the problems that hinder benefits brought by distributed energy production in microgrids, and then design an architecture based on artificial intelligence (AI) to address these challenges. Furthermore, a simulation framework is designed and useful data is adopted to build AI capabilities within energy utilities. In addition, a scalable framework that applies deep learning techniques is also implemented. Based on it, the AI inference at nodes and sensors in edge is realized to optimize the benefits brought by microgrids at different scenarios including community, enterprise and campus levels in smart cities.

## Computer Vision

Luo *et al.* [10] jointly optimize quality of experience (QoE) and energy consumption for video streaming in software-defined mobile networks. Specifically, a mechanism is proposed to jointly consider video quality adaption, buffer dynamics, video transcoding, edge caching and transmission. The time-varying channel is assumed as a discrete-time Markov chain, based on which two optimization problems are formulated as a Markov decision process (MDP) and a constrained MDP. A Lyapunov technique is adopted to transform a constrained MDP into regular one, which is further solved by an asynchronous advantage actor-critic algorithm. Then, the energy saving is achieved while QoE is also enhanced. Xu *et al*. [55] present an efficient CNN to reconstruct speckle image in cloud-edge computing for better image resolution with fewer inputs. A self-back stacked efficient residual factorized network is designed to reconstruct image through scattering medium. It includes two training stages, and the model is used for analyzing speckle image from low resolution to high one. Results show that a high resolution is achieved even if there are a small input samples. Lim *et al*. [38] propose an energy-efficient communication method in edge computing with deep learning, and it decreases power consumed by image transmission using edge computing. An energy-efficient IoT camera called CamThings is implemented by using the proposed communication and periodic on-off scheduling. CamThings performs better than the method that only adopts periodic on-off scheduling with respect to lifetime and power consumption. Zhang *et al*. [54] propose an offloading prediction algorithm to minimize real-time transmission of images. It predicts the future need for deep learning of each unmanned aerial vehicle (UAV), and transmits images only when necessary. Holistic allocation of resources is determined at edge according to the likelihood analysis of offloading for multiple UAVs. Monburinon *et al*. [68] present a hierarchical image recognition system based on edge computing, and its major processing is implemented at Raspberry Pi. A dynamic learning method is implemented and a convolutional neural network is trained to achieve recognition of animals in a specific environment. The recognition module is deployed in edge servers on gateway devices for performing offline image classification.

## Mobile Edge Computing (7)

Jin *et al*. [17] investigate a multi-user MEC system and propose computation offloading and resource allocation policies with the objective of minimization of energy consumption and service delay in a dynamic environment. An optimization framework is proposed based on deep reinforcement learning to maximize long-term cumulative rewards. Zhu *et al*. [44] propose a computation offloading mechanism to decrease completion time of applications and energy consumed by user devices. The formulated computation offloading problem is transformed into a time and energy optimization one. The optimal cost strategy is obtained with deep Q-learning. It outperforms local execution and random offloading with respect to energy consumption and completion time of service workflows.

Wang *et al*. [18] propose a DRL-based offloading framework to solve problems of task adaption and dependency in dynamic scenarios. It well learns an offloading policy represented by a sequence-to-sequence neural network. The offloading policy is inferred by automatically finding common patterns in different applications in various scenarios. Li *et al*. [23] investigate a multi-user MEC system in which many user equipments (UEs) realize computation offloading through wireless channels connected to an MEC server. The weighted cost of energy consumption and delay for UEs is formulated as an optimization objective. The offloading and allocation of computational resources are jointly optimized in an MEC system. A reinforcement Learning-based optimization framework is proposed by adopting Q-learning schemes. Zhang *et al*. [72] design an offloading framework for a network architecture including an MEC server and a mobile user based on deep reinforcement learning. The task flow offloading process is modeled as a Markov decision process. It aims to minimize the weighted sum of power consumption and offloading latency, which is transformed into the reward in each time slot. Yang *et al*. [30] consider a problem of joint minimization of energy and latency for hierarchical machine learning task distribution in mobile edge computing. The shallow neural network models are embedded in mobile devices in the framework. The computing-intensive and latency-sensitive tasks are offloaded to a nearby MEC server, which supports a deep neural network model. A piecewise convex optimization problem is formulated to minimize the weighted-sum of energy and latency. Then, a closed-form solution for an optimal strategy of partial offloading is obtained analytically. Dong *et al*. [21] investigate a mobile edge computing system supporting both low-latency and ultra-reliable communication services and delay tolerant ones. The normalized energy consumption is minimized by optimizing resource allocation, user association and offloading probabilities while meeting quality-of-service needs. A deep learning (DL) architecture is proposed and it is trained in a central server. An optimization algorithm is proposed to obtain the optimal offloading and resource allocation.

## Smart Grid (5)

Cheung *et al*. [16] .

To facilitate deep penetration of solar energy in smart grids, we need high observability of solar generation at the edges of the grid. Current advanced metering infrastructures (AMI) only monitor the aggregated measurements from net-metered households, but disaggregated consumption and solar generation components are required for grid optimizations. We propose an unsupervised disaggregation model for disaggregating solar generation from AMI measurements without the need of training data. The model requires only AMI measurements from consumers in a region and the solar irradiance as input, and models the consumption of consumers by neighboring households without rooftop photovoltaics (PV) to perform the disaggregation. We evaluate our results on a real life dataset from Austin, Texas. We show that our model is able to disaggregate consumption and solar generation measurements with 42.24% and 31.67% less mean squared error, respectively, in comparison to a baseline technique that uses supervised learning. This shows that our model is capable of disaggregating historical data even if the dataset has no training data and only contains minimal exogenous data.

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## Healthcare system (5)

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## Smart Cities (5)

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# DNN-based mechanisms for energy optimization

## DNN compression (5)

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[20] pCAMP compares the packages’ performances (with respect to the latency, memory footprint, and **energy**) [4]. resulting from five edge devices and observes that no framework could win over all the others at all aspects. It indicates that there is much room to improve the frameworks at the edge. Currently, developing a lightweight, efficient, and high-scalability framework to support diverse deep learning modes at the edge cannot be more important and urgent. Based on the application, certain optimizations can also be employed at run-time to reduce the number of samples to be processed. For example, in case of object detection application [58], a high-resolution image can be divided into multiple smaller images (known as tiling) and a selection criterion can be applied to select images with high activity regions. This process enables us to design DNNs which accept smaller inputs and thus are more computationally and latency-wise efficient.

DNN compression is an attractive solution to reduce the complexity of a given network. The work of [14] proposed a 3-step method (pruning, quantization and encoding) to significantly reduce the memory footprint of a given DNN. Network pruning was first used in [10] to reduce the number of connections. Several different pruning methodologies have been explored in the literature Different magnitudebased pruning methods are shown in Figure 2. Structured pruning [75] employs constraints on some DNN parameters (e.g., kernel, filter, channel) to maintain a certain structure. Another approach is to prune the redundant and least significant weights, regardless of the structure of the DNN itself [15] [45], and share the weights to reduce the dimensionality [14]. Other compression methods, based on variational dropout [44], knowledge transfer [24] and low-rank approximations [70] are promising as well. On the other hand, techniques which are focusing on reducing the precision, like quantization [79] [71], binarization [54] and approximate computing [4] [44] have to leverage the trade-off between accuracy and efficiency.

Hardware Accelerators: The optimizations at the software level should be supported by specialized hardware accelerators in a codesign fashion [47] [19]. Recent advances in the datacenter computing deep learning [27] have inspired accelerators for edge devices. Specialized accelerators like [5] [28] exploit the concurrency and the parallelism available in the processing of the DNNs, especially for convolutional leyers, while [20] takes care also of the fully-connected layers. These architectures, however, accelerate dense DNNs, and cannot exploit the sparsity introduced by pruning. Therefore, specialized accelerators for sparse DNNs are required [13] [52]. Challenging aspects of these accelerators are flexibility, reconfigurability and data reuse [35] [39] [65]. Moreover, particular types of DNNs, like CapsuleNets [60] and GANs [91]present several differences in the computation patterns, as compared to traditional DNNs. These challenges are addressed by their specialized accelerators. For example, CapsAcc [46] adopts a data reuse policy to efficiently process the routing-by-agreement algorithm on a systolyc array-based accelerator for CapsuleNets, and GANAX [76] propose a unified MIMD-SIMD design for concurrent execution of GANs. The software-level optimizations mainly include network pruning (Step-1 in Fig. 3) and quantization (Step-2 in Fig. 3) of the parameters.

## DNN partitioning (5)

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## Power/Battery Management (7)

[22]. Recently, distributed sustainable data centers based on **renewable** power generators have been deployed in order to efficiently reduce both the energy cost and carbon emission. The proposed method adopts long short-term memory approach to improve the prediction accuracy of renewable power capacity for a long period, and unsupervised deep learning (DL) solver to resolve the coordinated DRS/FS optimization.

[24] we study the dynamic MEC-access control problem for maximizing the long-term average uplink transmission rate whilst minimizing the transmission energy consumption for green IoT networks, in which the IoT device is powered by a rechargeable battery that can harvest energy from the surrounding environments.

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## Resource Allocation (9)

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## Computational offloading (8)

In order to achieve lower average task’s latency and energy consumption, we minimize the weighted summation of the average task’s delay and energy consumption by optimizing the task’s offloading decision [91].

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## DNN hardware architecture (9)

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## DNN packages and tools (11)

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Neurosurgeon [5] is a lightweight scheduler that can automatically partition DNN computation between mobile devices and datacenters at the granularity of neural network layers. By effectively leveraging the resources in the cloud and at the edge, neurosurgeon achieves low computing latency, **low energy consumption**, and high traffic throughput.

FPGA-based accelerators can achieve high-performance computing with low energy, high parallelism, high flexibility, and high security [6].

An efficient speech recognition engine (ESE) is designed to speed up the predictions and save energy when applying the deep learning model of LSTM. ESE is implemented in a Xilinx XCKU060 FPGA operating at 200 MHz. For the sparse LSTM network, it can achieve 282 GOPS, corresponding to 2.52 tera operations per second (TOPS) on the dense LSTM network. In addition, energy efficiency improvements of 40× and 11.5× are achieved, respectively, compared with the CPU- and GPU-based solution [7].

NVIDIA Jetson TX2 is an embedded AI computing device, which is designed to achieve low latency and high power efficiency. It is built upon an NVIDIA Pascal GPU with 256 CUDA cores, an HMP Dual Denver CPU, and a Qualcomm ARM CPU. It is loaded with 8 GB of memory and 59.7 GB/s of memory bandwidth and the power is about 7.5 W. The GPU is used to execute the deep learning task, and CPUs are used to maintain general tasks. It also supports the NVIDIA Jetpack SDK that includes libraries for deep learning, computer vision, GPU computing, and multimedia processing [8].

Edge TPU is Google’s purpose-built ASIC for edge computing. It augments Google’s Cloud TPU and Cloud IoT to provide an end-to-end infrastructure and facilitates the deployment of customers’ AI-based solutions. In addition, Edge TPU can combine the custom hardware, open software, and state-of-the-art AI algorithms to achieve high performance with a small physical area and low power consumption [9].

Prevalence of internet of things (IoT) enabled applications provide a new opportunity to low-cost FPGA devices to act as edge computing neural network nodes. Although FPGA vendors provide neural network development environments, they often target high-end devices. At the same time these development platforms are not as user friendly as their software counterparts. In this work we introduce ZyNet, a Python package, which enables faster implementation of deep neural networks (DNNs) targeting low-cost hybrid FPGA platforms such as the Xilinx Zynq. Based on hardware-software co-design approach, this platform supports pre-trained or on-board trained networks with development environment very similar to the popular TensorFlow. Implementation results show that the DNNs generated by the platform achieve accuracy very close to software implementations at the same time gives throughput by an order of magnitude compared to other edge computing devices at lower energy footprint. The platform is integrated with Xilinx development tools and is distributed as open source.

# NEW TRENDS AND OPEN CHALLENGES (Duplicated papers)

OPEN RESEARCH CHALLENGES

**Hardware Software Co-Design**: A common trend is to optimize the DNN for achieving high accuracy, without caring much about the underlying hardware complexity and energy consumption of a computing device. On the other hand, hardware designers have to implement a-posteriori architectures to exploit the software-level optimizations. However, hardware-aware software-level optimizations, e.g., for DNN architecture exploration [69] or compression [43] are promising and need further efforts to succeed. [20].

**In-Memory Computing**: It seems to be a promising paradigm for developing accelerators that can offer orders of magnitude of energy-efficiency gains compared to the conventional CPU and GPU based systems. However, the high variation characteristics associated with ReRAM and other non-volatile memories limit the accelerators which are based on them to offer precise functionality. Towards this, the multi-level cell (MLC) ReRAM technology has to be mature enough to offer reasonable precision while offering high data density. Also, a significant amount of work is required to develop methods which can be used to train networks such that they can offer high accuracy even when operated on NVM-based in-memory computing devices. [20].

**Hardware-Aware Hyperparameter Tuning and DNN Architectural Exploration**: Several software-level optimization techniques have been proposed which highlight that sparse DNNs, i.e., having lesser number of parameters, can also offer nearly the same level of output accuracy as dense DNNs. Systematic methodologies are required which, while being aware of the underlying hardware architecture and the system, can tune the network such that it offers near-optimal energy and performance efficiency while maintaining the baseline accuracy. [20].

Event-based Spiking Neural Networks: They have the potential to be much more energy-efficient, as compared to digital-based DNNs, because the power is only consumed when a spike is firing. Such event-driven processing are promising. Therefore, companies like IBM and Intel are investing into their respective neuromorphic architecture chips and its accelerators [48] [9]. [20].

## Distributed and Collaborative DNN

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## Relationship to SDN and NFV Technologies

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## Management and Scheduling of Edge Compute Resources

## Emerging Technologies

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## Deep Learning Benchmarks on Edge Devices

# CONCLUSION

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