Exploring Task Placement for Edge-to-Cloud Applications using Emulation

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Abstract—A vast and growing number of IoT applications connect physical devices, such as scientific instruments, technical equipment, machines, and cameras, across heterogeneous infrastructure from the edge to the cloud to provide responsive, intelligent services while complying with privacy and security requirements. However, the integration of heterogeneous IoT, edge, and cloud technologies and the design of end-to-end applications that seamlessly work across multiple layers and types of infrastructures is challenging. A significant issue is resource management and the need to ensure that the right type and scale of resources is allocated on every layer to fulfill the application’s processing needs. As edge and cloud layers are increasingly tightly integrated, imbalanced resource allocations and sub-optimally placed tasks can quickly deteriorate the overall system performance. This paper proposes an emulation approach for the investigation of task placements across the edge-to-cloud continuum. We demonstrate that emulation can address the complexity and many degrees-of-freedom of the problem, allowing us to investigate essential deployment patterns and trade-offs. We evaluate our approach using a machine learning-based workload, demonstrating the validity by comparing emulation and real-world experiments. Further, we show that the right task placement strategy has a significant impact on performance — in our experiments, between 5% and 65% depending on the scenario.

Index Terms—Edge, cloud, IoT, resource management, emulation.

I. INTRODUCTION

The Internet-of-Things (IoT) is driving the current data deluge to unprecedented scales. Howell [1] predicts that the number of IoT devices worldwide will grow annually by 12% to 125 billion in 2030. As these devices continuously produce data, the need to process and respond to this data in real-time is increasing. IoT devices and real-world processes often need to tightly integrate to enhance situational awareness, enable real-time decisions, and the steering and control of devices. Thus, a timely response is often essential. IoT has become the driving force behind the development of distributed infrastructures for data generated by scientific experiments and observatories, such as light sources [2], earth observatories [3], astronomy observatories [4], and the Large Hadron Collider [5].

While centralized cloud and high-performance computing (HPC) infrastructures address many computational requirements, they have limitations [6]. In particular, IoT scenarios require the management of voluminous data and are challenged by latencies, bandwidths, privacy, sovereignty, and cost requirements. Simultaneously, the types of infrastructures in the continuum are diversifying, e.g., increasingly powerful and heterogeneous IoT devices [7], [8], gateway servers, local compute infrastructure, and centralized clouds. This landscape of infrastructure is commonly referred to as the edge-to-cloud continuum (abbrev. continuum). It opens the possibility of bringing processing closer to the data source, thereby addressing the mentioned challenges [9].

However, utilizing and exploiting the edge-to-cloud continuum capabilities is hindered by a lack of understanding of application requirements and patterns, particularly concerning infrastructures and resource management. This paper provides an in-depth characterization of edge-to-cloud applications, studying common application characteristics and deployment modalities. Although edge-to-cloud applications often vary in many technical details, they share commonalities, e.g., in how they deploy and distribute machine learning pipelines across the continuum. Our analysis supports both application and tools developers in designing and building applications and tools that build on these characteristics and patterns.

Distributed resource and task management are crucial to satisfy applications’ performance and scalability requirements. There are important questions that applications need to consider for optimizing their task placements: How to partition an application workload across multiple layers of infrastructures? How many resources should be allocated on what layer? How should the application respond to changes in the available resources?

Thus, the ability to explore important task management trade-offs along the edge-to-cloud continuum is crucial. Often, only a subset of these factors can be evaluated using experiments. Extensive experimentation is often prevented by the availability of infrastructure and not time- and cost-effective. An important method that addresses these challenges is emulation, which allows the investigation of different aspects of IoT systems with a significantly reduced effort.

We utilize the RADICAL-DREAMER [10] emulation framework for modeling task placement in edge-to-cloud applications. Particularly, we evaluate workload and resource management aspects of edge-to-cloud applications, e.g., effective strategies for distributing workloads. Using the framework, we assess important metrics, e.g., time-completions broken down by different processing stages. We demonstrate our approach using extensive emulation experiments on XSEDE to investigate workload and task placements for different deployment modalities.

This paper is structured as follows: We discuss application
scenarios and characteristics in section II. Section III describes the emulation approach. We provide an extensive evaluation in section IV. Finally, section V discusses related work.

II. APPLICATIONS SCENARIOS AND REQUIREMENTS

Edge-to-cloud applications are highly diverse. Data scales, rates, and usage modes (edge-only, cloud-only, hybrid/edge-to-cloud) can vary significantly. However, they share many commonalities, e.g., the need to use the continuum to address performance, security, and privacy. We focus on IoT applications, i.e., applications that manage complex data processing pipelines across the edge-to-cloud continuum and discuss common patterns. We analyze different application scenarios from different application domains with the objective to identify common patterns.

A. Applications Scenarios

IoT devices are increasingly deployed in many scientific and industrial domains to allow data collection and analytics, improve process efficiencies, support remote operations and real-time control. Examples are large-scale scientific instruments and observatories found in many sciences (e.g., astrophysics, earth sciences), health care, farming, energy, mobility, factories, and supply chain (see Chabas et al. [11]). In the following, we investigate three application domains: farming, manufacturing, and scientific experiments.

Agriculture: IoT and data analytics help understand essential aspects of agriculture, e.g., energy, water usage, and yields [12]. An example is the usage of weather data and IoT data from the vineyard, such as environmental conditions and wine stress, to better guide the water irrigation system of the wine yard, reducing water usage [13]. Data collected from farms can be highly heterogeneous, e.g., spectral data for monitoring wine fermentation process, sound data for localization of livestock, and image data from cameras, drones, satellites.

Manufacturing: IoT sensors are also increasingly used in manufacturing environments. Data collected in such environments is crucial for use cases, such as predictive maintenance and visual inspection, planning, and optimization [14], [15].

Scientific Experiments and Facilities: Edge and fog capabilities are increasingly important for many scientific experiments, e.g., synchrotron light source experiments. Experimental facilities like the National Synchrotron Light Source II (NSLS-II) or the X-Ray Free Electron Laser (XFEL) are generating data at growing rates of up to 20 GB/sec [2]. This data often needs to be processed in a time-sensitive fashion, e.g., to either steer the experiments or update its digital twin [16]. In earth and environmental sciences, edge computing is a crucial enabler for increasing the impact of observatories. For example, the Atmospheric Radiation Measurement (ARM) facility envisions the in situ coupling of ARM observations with atmospheric and climate models on the edge to accelerate the time-to-insight [3].

B. Application Characteristics

In Table I, we use five categories to characterize application scenarios: sensing, data, processing, edge-to-cloud usage, and data exchange.

Sensing describes the process of capturing changes in the environment using sensors, e.g., for images, sound, temperature. Often, a specialized embedded CPU is used to perform this task. Often, some basic pre-processing is conducted during the sensing process to extract relevant events from the time-series raw sensor data. The data category describes the data characteristics, in particular, data types.

Processing characterizes the algorithms used for extracting insight from data, e.g., machine learning and analytics algorithms. Depending on the used approach, e.g., analytics with simple statistics or deep learning, different computational characteristics arise [17], [18]. In the context of machine learning, the processing characteristic can be differentiated in model

| Description | Farming | Manufacturing | Scientific Experiments |
|-------------|---------|--------------|-----------------------|
| Collection of spatial, temporal sensor data from the farm to enable optimizations, e.g., water, fertilizer usage. | Usage of IoT and machine data for improving process efficiencies, e.g., predictive maintenance and supply chain. | Usage of internet-connected instruments in different science domains, e.g., astronomy, high-energy physics, light source sciences |
| Manufacturing: Edge-to-Cloud Application Domains: | | |
| Sensing | Electric conductivity, temperature, microphones, cameras, spectrometers, weather | Logs, errors, vibration, temperature | Highly-specialized sensors built for specific experiments, high data rates, e.g., light source (up to 20 GB/sec) |
| Data | Time series sensor data, sound, images | Time Series sensor data, sound, image | Highly specialized data, e.g., light source raw data, astronomy. High volumes of historical data. High data rates during campaigns. |
| Processing | Outlier detection, feature extraction, image recognition, sound detection, anomaly detection | Outlier detection, image classification, object detection | Outlier detection, image reconstruction, image classification, object detection |
| Edge-to-Cloud Continuum | Edge: sensing & data collection, compression, monitoring Cloud: analytics, machine learning | Edge: sensing & data collection, compression, monitoring, process control Cloud: analytic, machine learning | Edge: sensing & data collection, compression, monitoring, steering Cloud: analytics, machine learning, simulation, optimization |
| Data Exchange | Edge-to-Cloud: Send only relevant data from edge-to-cloud | Edge-to-Cloud: Send meta-data and selected raw data for ML training selected amount from edge to cloud. Cloud-to-Edge: ML inference results | Edge-to-Cloud: Send meta-data and selected raw data for ML training selected amount from edge to cloud. Cloud-to-Edge: ML inference and simulation results for steering and control |

TABLE I: Edge-to-Cloud Application Domains: While IoT application domains are highly diverse, applications share the need for processing sensor data (e.g., image, sound) across multiple tiers of computing and data infrastructure.
training and inference. Further, pre-processing is essential to reduce the data volume and prepare for further processing, e.g., pre-aggregation, normalization, and sampling.

Table II describes the characteristics of the different types of processing workloads: pre-processing, analytics, inference and training. Depending on the choice of algorithm, the computational demands can vary significantly. A well-balanced system requires careful tuning of compute resources, bandwidths and algorithms.

Edge-to-Cloud describes how the applications is utilizing cloud and edge resources. Cloud capabilities allow for more intelligence (global analytics), improved model quality through the ability to use more complex models, and performance (more data and compute available). Data exchange characterizes data transmission patterns along the continuum.

C. Towards Application Patterns

While the application scenarios differ significantly, they share commonalities concerning the need to process sensor data, e.g., image, and sound, across multiple tiers of infrastructures. A re-occurring pattern is processing this data across multiple hierarchical layers of edge and cloud resources [19].

Figure 1 illustrates three common deployment modalities: cloud-, edge-centric and hybrid for distributing processing tasks across the continuum. In the cloud-centric modality, most services and tasks are run in the cloud; in the edge-centric modality on the edge. However, depending on the application scenario and available infrastructure, it is often beneficial to distribute tasks across the continuum utilizing a hybrid deployment modality.

On the edge, the focus is often on sensing, pre-processing, and compression; the cloud and intermediate layers (also referred to as fog) compute more advanced, global data aggregations, including machine learning inference and modeling. For example, while real-time applications often require inference on the edge to ensure low latencies, these edge capabilities often benefit from up-to-date models trained and updated using data collected from devices using advanced computational resources in the cloud. Another hybrid usage mode is the cloud usage for processing regions of interest identified using an edge-capable model, e.g., an anomaly detector. Often, cloud processing can accommodate more compute-intensive high-fidelity models.

Defining a suitable task placement strategy requires the consideration of various application and infrastructure characteristics and their interactions. In the following, we explore emulation as means to explore different task placement strategies.

III. WORKLOAD AND RUNTIME EMULATION

Distributed infrastructures encompassing the edge and cloud are complex, heterogeneous, and dynamic, making top-down designs and resource allocation decisions complicated. Thus, it is essential to evaluate potential decisions and their impact on the performance before real-world deployment. To address this issue, we use RADICAL-DREAMER (Dynamic Runtime and Execution Adaptive Middleware Emulator) [10] to evaluate deployment modalities, performance trade-offs and workload placement decisions for edge-to-cloud applications [20]. In the following, we describe the fundamental components and their interactions of the framework.

Table III provides an overview of the concept used by the emulator. The emulator requires two inputs: (i) the workload and (ii) the resources. A workload is defined as a collection of tasks that are submitted to the emulator. A resource’s capacity is defined by the number of cores and the supported throughput on operations per second. Multiple resources can be grouped. Further, the emulator allows the modeling of delays, e.g., induced by network latencies.

The emulator is capable of accommodating both application and infrastructure variability. For example, an ensemble of heterogeneous tasks can be modeled using the ops_dist attribute of a workload, which accepts different distributions, e.g., normal or uniform distribution. This feature is important to model, e.g., variabilities that arise in the processing times

| Task   | Description of an application (e.g., ensembles of heterogeneous/homogeneous tasks) and Resource to model distributed infrastructure. The Session and ResourceManager are used for the emulation execution. |
|--------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Resource | Description of the entity that is executing a given workload. A resource is defined by three parameters: the number of cores, each core’s capacity defined as the number of operations per core, and a delay. Variability in the performance can be modeled using a statistical distribution. |
| Session | Orchestrates emulation runs across multiple resources. |

### TABLE II: Typical Characteristics of the Different Types of Processing Tasks

| Task    | Compute | Memory | I/O |
|---------|---------|--------|-----|
| Pre-processing | 0       | +      | ++  |
| Analytics    | +       | +      | +   |
| Inference    | ++      | ++     | +   |
| Training     | +++     | +++    | +   |

### TABLE III: RADICAL-DREAMER Concepts

| Concept | Description |
|---------|-------------|
| Session | Manages the application run via Resource Manager. |
| Resource Manager | Orchestrates emulation runs across multiple resources. |
| Task     | Abstracts a computational process to be executed. A task is characterized by a num_ops, i.e., the number of operations required to compute. Variability in the performance can be modeled using a statistical distribution and the ops_dist parameter. |
| Workload | Collection of tasks submitted to the emulator at a time. |
due to imbalanced datasets. Similarly, performance variability and heterogeneous resources can be emulated using the \texttt{perf_dist} attribute of a resource.

The \texttt{Session} object functions as an entry point and accepts a workload, resource, and schedule configuration as input. The \texttt{ResourceManager} handles the execution of the workload on the defined resources. Session and Resource Managers communicate via a RabbitMQ service. The \texttt{Session} records the execution and documents the results, e.g., the execution times of each task and the time-to-completion (TTC), so that these can be analyzed posterior to the experiment.

The emulator provides the ability to investigate different resource configurations, scheduling policies, application algorithms, parallelization, and distribution strategies. The costs per emulation run are very low, allowing broad explorations before setting up real-world systems and experiments.

IV. EXPERIMENTS

Insights into the complex and dynamically varying edge-to-cloud systems’ performance characteristics are crucial to ensure appropriate response times, throughput and to optimize resource usage. In this section, we evaluate our emulation approach using a machine learning application using the K-Means algorithm. For this purpose, we compare the performance of a real-world execution with the emulated performance. We use the XSEDE Jetstream cloud [21] and two different virtual machines (VM) types: a single-core VM with 2 GB of memory (edge), which is comparable to a Raspberry Pie, and a 44 core VM with 120 GB of memory (cloud).

The K-Means [22] algorithm is a popular unsupervised machine learning algorithm that groups related data points in a dataset to discover underlying patterns. We model a K-Means application with the emulator and compare it to a real-world execution. For this purpose, we use the Scikit-Learn K-Means implementation with one core [23]. The complexity for a K-Means algorithm is \( O(KNT) \), where \( K \) is the number of clusters, \( N \) is the number of points in the dataset, and \( T \) is the number of iterations for a single run.

The K-Means application is translated to a workload of \( T \) tasks, where each task represents an iteration of the algorithm. Based on the number of points and clusters \((KN)\) in each iteration, we compute the number of operations per task. Each iteration is then mapped to a task. The resource’s capacity defined by the supported operations per second is derived from an XSEDE Jetstream cloud micro experiment. We then calculate the operation per second executed for the given input data size, i.e., from 32 to \(10^6\) points, and configure the emulator’s workload and tasks accordingly.

We conduct an end-to-end experiment to evaluate task placement strategies for an edge-centric and cloud-centric scenario. Further, we assess the quality of the emulated time-to-completion (TTC) by comparing it to real experiments. For the cloud scenario, we use a Kafka broker to move data from the edge to the cloud.

Figure 2 shows the results of the evaluation. As shown, we can capture real-world behavior with our emulation approach.

![Figure 2: Edge-to-Cloud K-Means – Experiment and Emulation for Cloud- and Edge-Centric Deployment Modalities](image)

As seen in the upper inset, the limited edge resources can outperform the cloud for smaller data sizes (<30k points). In this case, the overhead for setting up data transfers to the cloud too large, particularly compared to the compute time. As the data size increases, the computational demands grow, making it advantageous to move the data to the cloud.

Further, we investigate the relationship between the number of clusters for K-Means and TTC using a configuration with a fixed \(10^6\) data points (see lower inset in Figure 2). As the cluster size increases, K-Means algorithm’s complexity grows, leading to a longer TTC. In summary, both experiments validate that the used emulation approach is suitable for capturing important characteristics of real-world applications.

When comparing edge- vs. cloud-centric task placement strategies, the experiments demonstrate that the right task placement has a significant impact on the overall performance. For smaller data sizes, we observed up to 65\% better performance on the edge devices; for larger data sizes, the cloud runtime was up to 10\% faster.

V. RELATED AND PREVIOUS WORK

Varshney/Simmhan [24] provide an extensive survey of application programming and scheduling models for the edge-to-cloud continuum. Ref. [25], [26] review various emulation approaches for specific aspects of the edge-cloud continuum that have emerged, e.g., focusing on network, compute, scheduling, or data. We focus on a narrow approach of using emulation for application-level task placement strategies.

CloudSim [27] is a well-known simulator for cloud infrastructures and supports, e.g., federated infrastructures. The objective of CloudSim is to support resource management and scheduling decisions. Several extensions for edge computing emerged, e.g., IoTSim-Edge [28] provides a comprehensive framework for modeling edge-to-cloud continuum environments. It allows the modeling of environments considering, e.g., (i) different IoT communication protocols, (ii) edge device heterogeneity, (iii) data movements, and (iv) energy.
While these emulation approaches are often feature-rich and support broad objectives, they are typically focused on infrastructure, considering application characteristics only on very abstract levels. We specifically address IoT and data-driven applications that require complex, distributed data processing pipelines with highly dynamic data movements and computational requirements.

 VI. CONCLUSION AND FUTURE WORK

Designing distributed applications that need to handle data and computing across multiple infrastructure layers is challenging. This paper presented a comprehensive emulation approach for characterizing and understanding edge-to-cloud applications. Emulation allows exploring vast parameter spaces and is an essential tool to guide experimental design, and experimentation is crucial to evaluate end-to-end performance data across all layers. Additionally, the emulator allows the quick investigation of ‘what-if’ scenarios.

We demonstrated these capabilities by studying important resource management challenges, e.g., the suitability of a machine learning model for a given scenario. For example, in our experiments, we investigated the impact of model complexity on latencies.

In the future, we will develop abstractions for distributed edge-to-cloud applications that provide the means to devise and implement effective resource management strategies. The envisioned Pilot-Edge abstraction is based on the pilot abstraction [29]. It provides an easy-to-use serverless Function-as-a-Service API that simplifies application development, allowing developers to focus on application logic and application-level resource management. It supports common patterns, e.g., cloud-centric, edge-centric, and hybrid applications. Tasks can easily be moved to different parts of the continuum, e.g., from the edge to the cloud, or vice versa. Further, we will tightly integrate our emulation approach with the Pilot-Edge middleware providing the ability (i) to include parameters from real-world experiments and (ii) to use the emulation to optimize the experiment’s design.

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