Pilot-Edge: Distributed Resource Management Along the Edge-to-Cloud Continuum

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Abstract-Many science and industry IoT applications necessitate data processing across the edge-to-cloud continuum to meet performance, security, cost, and privacy requirements. However, diverse abstractions and infrastructures for managing resources and tasks across the edge-to-cloud scenario are required. We propose Pilot-Edge as a common abstraction for resource management across the edge-to-cloud continuum. Pilot-Edge is based on the pilot abstraction, which decouples resource and workload management, and provides a Function-as-a-Service (FaaS) interface for application-level tasks. The abstraction allows applications to encapsulate common functions in high-level tasks that can then be configured and deployed across the continuum. We characterize Pilot-Edge on geographically distributed infrastructures using machine learning workloads (e.g., k-means and auto-encoders). Our experiments demonstrate how Pilot-Edge manages distributed resources and allows applications to evaluate task placement based on multiple factors (e.g., model complexities, throughput, and latency).

Index Terms—Edge, cloud, IoT, abstractions, machine learning.

I. INTRODUCTION

A growing number of scientific [1], [2] and industrial applications [3], require the flexible use of resources along the *edge-to-cloud continuum (abbrev. continuum)*. The coupling of edge and cloud resources enables applications to address latency, bandwidth, sovereignty, privacy, and security requirements [4]. The integration of experimental instruments, machines, equipment, and other IoT devices, with multiple layers of infrastructures, comprising edge, HPC and cloud infrastructures, is critical to delivering value for these applications.

Machine learning (ML) methods are essential for deriving insights from the data produced from these applications. The combination of growing data volumes and high computational requirements of these ML applications has accelerated the need for more intelligent use of distributed computing resources in the continuum [5]. However, these workloads are highly complex, involving distributed data flows of metaand raw data, and the orchestration of inference and training tasks across the continuum. This complexity often results in highly monolithic applications with tightly coupled application and infrastructure code, limiting the scalability, reusability, and maintainability of the application.

The complexity, heterogeneity and geographic distribution of IoT, edge, and cloud infrastructures [4], [6] make it challenging to design applications, allocate appropriate resources, and manage workloads. Particularly, IoT applications are characterized by heterogeneous tasks, comprising a mix of real-time tasks for control and steering and long-running tasks for machine learning training and simulation. Thus, they need to optimize data and compute placement carefully. Many point and local solutions exist, which might suffice at small scales, but do not allow for scalable, end-to-end solutions that permit workload adaptivity and optimization. Complex application-specific architectures that integrate disperse technological components lead to unpredictable performance. Thus, it is essential to provide abstractions that abstract complexity and heterogeneity and enable applications to adapt to the dynamism induced by infrastructures, data, and other sources [7].

This paper introduces the *Pilot-Edge* abstraction and framework. Pilot-Edge is motivated by improved edge-to-cloud application development, deployment, and management. It provides a Function as a Service (FaaS) interface which abstracts resources from the application. Pilot-Edge allows applications to decompose workloads into tasks, and deploy them across the continuum. Pilot-Edge orchestrates tasks generated from the function code, handling placement and data movements transparently, considering application-defined preferences (e.g., data dependencies and preferred placements). Pilot-Edge relies on the pilot abstraction for distributed resource management and unified access to resources across all layers. We envision Pilot-Edge as providing the hierarchical but continuous resource management fabric for edge-to-cloud infrastructures, enabling many increasingly complex applications comprising heterogeneous multi-task workloads, and requiring diverse resource capabilities.

Pilot-Edge was designed based on an analysis of different IoT application scenarios (e.g., earth sciences, light source science [8]). It enables the effective handling of heterogeneous and dynamic workloads arising in IoT environments (e.g., seasonal peak loads, failures and other external events). Pilot-Edge allows applications to respond to dynamism, e.g., external events, load peaks, and resource failures, by updating their tasks' payload or acquiring additional resources. We characterize and demonstrate the capabilities of Pilot-Edge using extensive end-to-end experiments on geographically distributed infrastructure, particularly XSEDE (US) [9] and LRZ (Germany), and ML workloads, e.g., auto-encoders.

This paper is structured as follows: In section II, we present Pilot-Edge and provide an extensive evaluation of the framework in section III. Section IV discusses related work.

II. PILOT-EDGE: ABSTRACTION AND FRAMEWORK

Managing the edge-to-cloud continuum's complexity and dynamism requires a sophisticated framework that aids in managing resources and workloads. *Pilot-Edge* aims to simplify the development of edge-to-cloud applications by providing a high-level abstraction for developing, deploying, and managing computation and data across multiple layers of distributed infrastructure. After discussing previous work on the pilot abstraction in section II-A, we present Pilot-Edge's architecture and abstraction in sections II-B and II-C.

A. Previous Work: Pilot-Abstraction

Pilot-Edge is based on the pilot abstraction, an abstraction for distributed resource management [10]. The pilot abstraction is based on the observation that using a placeholder job to allocate a resource container is a re-occurring pattern used by many applications. The pilot abstraction decouples resource and workload management and supports manifold workloads, particularly workloads that require task parallelism on HPC and clouds. The term pilot refers to a placeholder job in a queuing system that allocates resources on which the application can execute tasks. A pilot generally refers to a dedicated resource set that an application owns, e. g., a virtual machine, a job partition (HPC), or a Lambda function [11].

While the pilot abstraction was designed for HPC, we extended it for data-intensive and streaming applications, which similarly exploit data parallelism. Pilot-Data added support for data management in conjunction with pilots. Further, we integrated frameworks for data processing [12], [13], such as Spark and Dask [14], and streaming [15], such as Kafka [16]. Pilot-Streaming also allows the event-driven execution of tasks on-demand, e. g., responding to data arrival events.

While the pilot abstraction is well suited for bridging heterogeneous infrastructures across the edge-to-cloud continuum and administrative domains, the current implementation has several limitations: (i) the provided abstraction is low-level, requiring applications to manage resources and wrap their workload into tasks, and (ii) the implementation is optimized for data-center-based infrastructure and workloads.

B. Architecture

Pilot-Edge extends Pilot-Streaming [15] and supports various resource types via a plugin-based architecture, e.g., HPC and cloud clusters (such as OpenStack, AWS), smaller IoT devices (via SSH). Further, Pilot-Edge extensively utilizes message brokering based on Kafka to manage edge-to-cloud streaming topologies. Brokering concerns are also encapsulated using a plugin mechanism. Support for further brokering framework, e.g., MQTT for low-performance and low-power environments, can easily be added.

Figure 1 illustrates the overall architecture (blue components extended in this work). A typical application comprises three stages: (step 1) allocating resources using the pilot abstraction, (step 2) running a distributed edge-to-cloud application, and (step 3) monitoring applications.

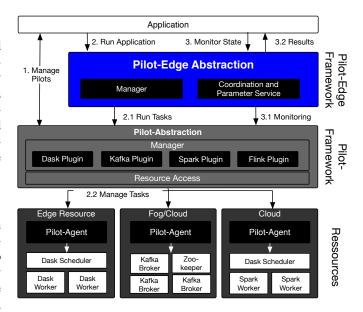


Fig. 1: Pilot-Edge Architecture and Interactions: Pilot-Edge comprises the Pilot-Edge framework and pilot framework. Applications acquire edge-to-cloud resources using the pilot framework in step 1. In step 2 applications configure Pilot-Edge using the resources acquired and submit their workload to the framework. Comprehensive monitoring services are provided (step 3).

As edge-to-cloud applications typically rely on highlyspecialized processing pipelines and resources, we currently require the manual allocation of resources via the pilot abstraction [10] (step 1 in Fig. 1). The pilot abstraction provides a common interface to allocate arbitrary resources, e. g., a RasPi, virtual machines located on the edge and cloud, serverless cloud functions, HPC machines. Thus, depending on the continuum layer, a pilot can represent different types of resources. Further, the pilot abstraction can manage brokering and data processing frameworks, e. g., Kafka and Dask. In summary, the pilot abstraction encapsulates much of the complexity of distributed resources. The created pilots are then used to initialize the application (step 2 in Fig. 1).

After submitting the application, Pilot-Edge translates and packages the user-defined functions into tasks to be executed on the edge, cloud, or HPC pilots (step 2). Further, it provides a central coordination and parameter service to share state, e.g., for data or machine learning models, across the continuum. Pilot-Edge automatically handles task placements, i.e., the binding of a task to a pilot (step 2.1).

The tasks are executed using a managed Dask [14] cluster on the specified location (step 2.2). The input data is passed as a parameter to each function; the output is captured with a return parameter. Further information on the resource topology and shared state are via a context object. A unique job identifier ensures that progress and errors can be consistently tracked across all components. The framework also manages the data movements using a pilot-managed Kafka broker and an automatically created Kafka topic. Further, it provides a Redis-based parameter server for sharing model weights across the continuum.

C. Pilot-Edge API

Pilot-Edge exposes a *Function-as-a-Service (FaaS) API*, that abstracts details about individual resources, allowing the application to focus on application logic and not infrastructure. While the framework is suited to support arbitrary IoT edge applications, we mainly focus on data and machine learning applications.

Listing 1: Pilot-Edge FaaS API

```
def produce_edge(context)
```

def process_edge(context: dict = None, data=None)

def process_cloud(context: dict = None, data=None)

Listing 1 illustrates the API of the Pilot-Edge-abstraction. The API is application-centric and lets developers focus on expressing important application tasks, e.g., sensing and inference, and on selected trade-offs, such as task localities. The API comprises three functions: (i) for managing sensing and data generation on the edge, (ii) for edge processing, and (iii) for cloud processing. While each task must be defined as a Python function, it is also possible to access native capabilities, e.g., by integrating native code for accessing low-level sensors on the edge. The API allows the re-use of functions across the continuum while retaining flexibility and customizability.

Listing 2: Pilot-Edge API: Instantiation of an Application

```
pilot.EdgeToCloudPipeline (
    pilot_cloud_processing=pilot_job_cloud_processing,
    pilot_cloud_broker=pilot_job_cloud_broker,
    pilot_edge=pilot_job_edge,
    produce_function_handler=produce_block_edge,
    process_edge_function_handler=process_block_edge,
    process_cloud_function_handler=process_block_cloud,
    function_context=context,
    ...
).run()
```

Listing 2 shows how an edge-to-cloud application is instantiated. In addition, to passing the function references to the data generation and processing functions, a references to the edge and cloud pilot is required. The framework then handles the dataflow between the instantiations of the defined functions in these pilots using Kafka.

D. Discussion

Pilot-Edge provides a blueprint for applications and supports common patterns, e. g., integrating sensing tasks, i. e., tasks that capture environmental changes using sensors, and other types of processing, e. g., pre-processing and machine learning inference. For example, commonly, the API's data source function (produce_edge in Listing 1) is used either to deploy data collection code, e. g., code for reading out a sensor or a data generator. The edge and cloud functions are used for processing. For example, the edge function frequently serves for data pre-aggregation, outlier detection, and data compression to ensure that the amount of data movement is minimal. The cloud functions are often used for more complex analytics, training, and modeling tasks.

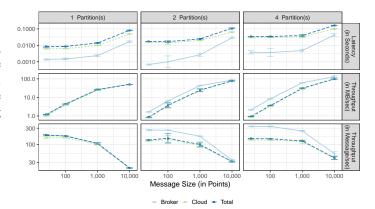


Fig. 2: Throughput and Latencies by Message Size and Partitions: The system's total throughput increases with the number of edge devices and partitions; every edge device is assigned a dedicated partition. In the four partition scenario, the processing system becomes the bottleneck determining the overall throughput.

By nature, edge-to-cloud applications are subject to different dynamism and variability induced by data sources, infrastructures, and applications. If supported by the resource, the allocated resources can be adapted, i. e., expanded and scaleddown, dynamically at runtime, e. g., if a bottleneck arises due to increased data rates or in response to an application event (e. g., the discovery of a significant data pattern). The processing functions can be programmatically replaced at runtime (without the need to allocate a new pilot), allowing, e. g., the exchanging low vs. high fidelity models.

III. EXPERIMENTS

This section conducts a performance characterization of different machine learning workloads using Pilot-Edge. For our experiments, we use the Leibniz Supercomputing Center (LRZ) und XSEDE Jetstream clouds and different VM types: 4 core/18 GB (medium), 10 cores/44 GB (large) (LRZ) and 6 cores/16 GB (medium) (Jetstream). Synthetic data is generated using the Mini-App data generator [11].

1) Baseline Performance: We investigate the throughput and latency with the edge data source, broker, and processing components deployed on the LRZ cloud. The edge devices are simulated with a Dask task, allocating one core and about 4 GB of memory, comparable to a current Raspberry Pi. We use one partition per edge device for simplicity and keep the ratio of partitions constant between Kafka and Dask. We use message sizes of 25 to 10,000 points with 32 features each. Every point has a serialized size of 8 Bytes, i. e., message sizes are 7 KB to 2.6 MB. We send 512 messages per run and repeat each experiment at least three times.

Figure 2 illustrates the baseline throughput and latencies. The framework captures and links comprehensive metrics across all involved components, particularly the edge data generator, broker, and cloud processing services (for clarity, data for edge is not displayed). This data allows the easy identification of bottlenecks. For example, for four partitions, it is apparent that the Kafka broker can process more data than the consuming processing tasks in the cloud.

2) Machine Learning Models and Geographic Distribution: We continue to evaluate three machine learning models for outlier detection. We primarily use the cloud-centric deployment pattern (see Figure 1 in [8]), i.e., we deploy the data generator on the edge and the processing tasks, which include pre-processing, training and inference, on the cloud. We evaluate three machine learning models: the auto-encoder, isolation forests, and k-means (25 clusters as previously). In all cases, the model is updated based on the incoming data; model updates are managed via the parameter service. We use the large VM on LRZ for all processing tasks (10 core/44 GB).

Isolation forests [17] are an ensemble technique where each task partitions the dataset randomly into trees. An outlier is defined by the number of steps required to isolate a data point; the fewer steps required, the more likely a point is an outlier. We use the PyOD [18] implementation and a default of 100 ensemble tasks. Auto-encoders [19] are unsupervised models that rely on a deep neural network to learn a data representation. For outlier detection, the reconstruction error is used to determine whether a data point is anomalous. We use the Keras-based auto-encoder implementation of PyOD with four hidden layers with a size of [64, 32, 32, 64], and thus, a total number of 11,552 parameters.

Figure 3 illustrates that as the computational complexity increases, the performance degrades significantly compared to the baseline case. Isolation forests achieve a significantly worse performance than k-means for both latency and throughput. Auto-encoders required careful tuning of the system; we had to adjust the memory and garbage collection. Due to their high resource demands, they are not suitable for streaming and require additional resources, e. g., GPUs. Alternatively, an edge or hybrid deployment would be an option.

Further, we investigate the geographic distribution and place the data source on Jetstream/XSEDE (US) and processing stages (i. e., pre-processing, training, and inference) on the LRZ cloud (Europe). The latency between both locations varied between 140 and 160 msec; bandwidth fluctuated between 60 to 100 MBits/sec (iPerf measurement). We use four partitions for this experiment. As expected, the overall throughput for the baseline and k-means scenarios is limited by intercontinental data transfer. Both scenarios would benefit from a hybrid edge-to-cloud deployment, e. g., by adding a data compression step before the data transfer. The results also show that the network is not the bottleneck for the compute-intensive models, i. e., auto-encoder and isolation forests.

IV. RELATED WORK

Apache Edgent [20] is an edge platform designed to integrate IoT devices and brokering systems, e. g., Kafka. Edgent is narrowly focused on the edge device and broker communication and does not consider resource management across the continuum holistically. Similarly, SpanEdge [21] is a stream processing system based on Apache Storm [22] that allows applications to run certain parts of a topology, a Storm processing pipeline, close to the data source. SpanEdge dependence

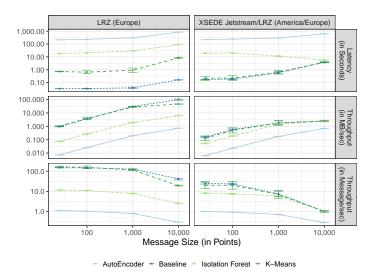


Fig. 3: Throughput and Latency by Model Type, Message Size, and Geographical Distribution: The model complexity significantly impacts all metrics. K-means outperforms isolation forests and autoencoders, which shows the worst performance and is not well suited for environments with limited resources.

on Storm limits its applicability in the heterogeneous continuum. The programming model lacks many aspects required for machine-learning-based applications, e. g., the integration with modern Python frameworks like Tensorflow and Dask.

Further, various Kubernetes-based frameworks emerged, e.g., MicroK8s and KubeEdge [23]. KubeEdge extends containerized application orchestration and device management to the edge. While Kubernetes is cloud-agnostic and provides some interoperability, it is also highly complex and designed for a stable cloud environment. Data-related concerns, such as data movements, are not transparently handled and need to be implemented on the application-level.

Different public cloud providers offer edge extensions for their serverless FaaS runtime. For example, Lambda Edge [24] enables the execution of Lambda function in Greengrass IoT runtimes. A similar offering exists on Azure with IoT Edge [25]. While FaaS is easy to use and benefits from the automatic resource management and scaling of clouds, these benefits do not apply necessarily to edge devices, subject to significant resource constraints. Further, several research frameworks that explore the usage of FaaS along the edge-to-cloud continuum emerged, e. g., CSPOT [26] and funcX [27].

While these related frameworks offer similar abstractions, Pilot-Edge differs in different aspects: (i) Pilot-Edge supports highly heterogeneous workloads and infrastructures, bringing together distributed resources and capabilities from different providers. (ii) By decoupling resource management and application-level scheduling, applications can better respond to dynamic changes in the environment. (iii) Pilot-Edge provides more flexible mechanisms to handle data and models across the continuum, e. g., by integrating brokering services for data streaming and coordination services for sharing machine learning models.

V. CONCLUSION AND FUTURE WORK

We presented Pilot-Edge, an abstraction for supporting data and ML applications in the edge-to-cloud continuum addressing the following challenges: (i) *Heterogeneity:* The edge-tocloud continuum is highly diverse, comprising many different types of hardware and software components that need to be unified and integrated, (ii) *Dynamism* in distributed, geographically disperse environments often constrains application leading to unacceptable and unpredictable performance. The ability to respond at runtime, e. g., by auto-scaling resources, is crucial, and (iii) *Performance* in distributed, heterogeneous environments can be highly unpredictable depending on shared resources, system loads, and data.

Pilot-Edge was designed based on an analysis of different applications and provides an easy-to-use FaaS API that simplifies application development, allowing developers to focus on application logic and application-level resource management. It supports common deployment modalities, e.g., more cloud-centric or edge-centric scenarios. Tasks can easily be moved to different parts of the continuum at runtime. Particularly, it supports common data collection, model training, and deployment patterns of ML-driven IoT applications.

Our experiments investigated various trade-offs, e.g., the impact of model complexity on the overall throughput. For example, k-means can achieve five times the throughput of isolation forests for large message sizes (10,000 points). Further, auto-encoders proved unsuitable for the investigated resource configurations due to their high computational demands. These insights provide valuable input for system design and deployment, allowing an optimal resource layout.

In the future, we will continue to extend Pilot-Edge and simplify the usage. For example, we will generalize the abstraction to arbitrary architectures and topologies of resources — currently, it is limited to two layers: edge and cloud. We envision Pilot-Edge as the basis for a distributed workload management system that can select, acquire and dynamically scale resources across the continuum at runtime based on the application's objectives. To further enhance our understanding of the continuum, we will explore novel edge-to-cloud scenarios, e. g., federated learning, and investigate further scheduling and approaches, e. g., energy consumption.

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REFERENCES

- Brookhaven National Laboratory. National synchrotron light source ii. https://www.bnl.gov/ps/, 2017.
- [2] Gary Geernaert. Earth and environmental systems: Strategic plan. https://science.osti.gov/~/media/ber/pdf/workshop%20reports/ 2018_CESD_Strategic_Plan.pdf, 2018.
- [3] A. Srivastava, S. Aggarwal, A. Apon, E. Duffy, K. Kennedy, A. Luckow, B. Posey, and M. Ziolkowski. Deployment of a cloud pipeline for realtime visual inspection using fast streaming high-definition images. *Software: Practice and Experience*, 50(6):868–898, 2020.
- [4] Pete Beckman, Jack Dongarra, Nicola Ferrier, Geoffrey Fox, Terry Moore, Dan Reed, and Micah Beck. *Harnessing the Computing Continuum for Programming Our World*, chapter 7, pages 215–230. John Wiley & Sons, Ltd, 2020.

- [5] R. Nishihara, P. Moritz, S. Wang, A. Tumanov, W. Paul, J. Schleier-Smith, R. Liaw, M. I. Jordan, and I. Stoica. Real-time machine learning: The missing pieces. *CoRR*, abs/1703.03924, 2017.
- [6] Michaela Iorga, Nedim Goren, Larry Feldman, Robert Barton, Michael J. Martin, and Charif Mahmoudi. Fog computing conceptual model. https: //doi.org/10.6028/NIST.SP.500-325, 2018.
- [7] S. Jha, D. S. Katz, A. Luckow, N. Chue Hong, O. Rana, and Y. Simmhan. Introducing distributed dynamic data-intensive (d3) science: Understanding applications and infrastructure. *Concurrency and Computation: Practice and Experience*, 29(8):e4032. e4032 cpe.4032.
- [8] Andre Luckow, Kartik Rattan, and Shantenu Jha. Exploring task placement for edge-to-cloud applications using emulation. In *Proceedings of* 5th IEEE International Conference on Fog and Edge Computing, Melbourne, Australia, 2021.
- [9] XSEDE. Jetstream user guide. https://portal.xsede.org/jetstream, 2020.
- [10] A. Luckow, M. Santcroos, A. Merzky, O. Weidner, P. Mantha, and S. Jha. P*: A model of pilot-abstractions. *IEEE 8th International Conference* on e-Science, 2012. http://dx.doi.org/10.1109/eScience.2012.6404423.
- [11] Andre Luckow and Shantenu Jha. Performance characterization and modeling of serverless and hpc streaming applications. In *Proceedings* of StreamML Workshop at IEEE International Conference on Big Data (IEEE BigData 2019), Los Angeles, CA, USA, 2019.
- [12] A. Luckow, I. Paraskevakos, G. Chantzialexiou, and S. Jha. Hadoop on HPC: Integrating Hadoop and Pilot-based Dynamic Resource Management. *IEEE International Workshop on High-Performance Big Data Computing in conjunction with The 30th IEEE International Parallel and Distributed Processing Symposium (IPDPS 2016)*, 2016. http://dx.doi.org/10.1109/IPDPSW.2016.166.
- [13] A. Luckow, M. Santcroos, A. Zebrowski, and S. Jha. Pilot-Data: An Abstraction for Distributed Data. *Journal Parallel and Distributed Computing*, October 2014. http://dx.doi.org/10.1016/j.jpdc.2014.09.009.
- [14] Dask: Library for dynamic task scheduling. http://dask.pydata.org, 2016.
- [15] A. Luckow, G. Chantzialexiou, and S. Jha. Pilot-streaming: A stream processing framework for high-performance computing. *Proceedings of* 14th IEEE eScience, 2018.
- [16] J. Kreps, N. Narkhede, and J. Rao. Kafka: A distributed messaging system for log processing. In *Proceedings of 6th International Workshop* on Networking Meets Databases (NetDB), Athens, Greece, 2011.
- [17] F. T. Liu, K. M. Ting, and Z. Zhou. Isolation forest. In 2008 Eighth IEEE International Conference on Data Mining, pages 413–422, 2008.
- [18] Yue Zhao, Zain Nasrullah, and Zheng Li. Pyod: A python toolbox for scalable outlier detection. *Journal of Machine Learning Research*, 20(96):1–7, 2019.
- [19] Charu C. Aggarwal. *Outlier Analysis*. Springer Publishing Company, Incorporated, 2nd edition, 2016.
- [20] Apache Software Foundation. Apache edgent (incubating). https: //edgent.incubator.apache.org/, 2020.
- [21] H. P. Sajjad, K. Danniswara, A. Al-Shishtawy, and V. Vlassov. Spanedge: Towards unifying stream processing over central and nearthe-edge data centers. In 2016 IEEE/ACM Symposium on Edge Computing (SEC), pages 168–178, 2016.
- [22] A. Toshniwal, S. Taneja, A. Shukla, K. Ramasamy, J. M. Patel, S. Kulkarni, J. Jackson, K. Gade, M. Fu, J. Donham, N. Bhagat, S. Mittal, and D. Ryaboy. Storm@twitter. In *Proceedings of the 2014 ACM SIGMOD International Conference on Management of Data*, SIGMOD '14, page 147–156, New York, NY, USA, 2014. ACM.
- [23] Kubeedge: An open platform to enable edge computing. https:// kubeedge.io/en/, 2021.
- [24] Amazon Web Services. Lambda@edge. https://aws.amazon.com/ lambda/edge/, 2020.
- [25] Microsoft. Azure IoT Edge: Cloud intelligence deployed locally on IoT edge devices. https://azure.microsoft.com/services/iot-edge/, 2020.
- [26] Rich Wolski, Chandra Krintz, Fatih Bakir, Gareth George, and Wei-Tsung Lin. Cspot: Portable, multi-scale functions-as-a-service for iot. In *Proceedings of the 4th ACM/IEEE Symposium on Edge Computing*, SEC '19, page 236–249, New York, NY, USA, 2019. ACM.
- [27] Ryan Chard, Yadu Babuji, Zhuozhao Li, Tyler Skluzacek, Anna Woodard, Ben Blaiszik, Ian Foster, and Kyle Chard. Funcx: A federated function serving fabric for science. In *Proceedings of the 29th International Symposium on High-Performance Parallel and Distributed Computing*, HPDC '20, page 65–76, New York, NY, USA, 2020. ACM.