arXiv:2106.13859v1 [cs.DC] 25 Jun 2021

rFaaS: RDMA-Enabled FaaS Platform for Serverless High-Performance Computing

Marcin Copik
marcin.copik@inf.ethz.ch
ETH Zürich
Switzerland

Konstantin Taranov
ETH Zürich
Switzerland

Alexandru Calotoiu
ETH Zürich
Switzerland

Torsten Hoefler
ETH Zürich
Switzerland

ABSTRACT

The rigid MPI programming model and batch scheduling dominate high-performance computing. While clouds brought new levels of elasticity into the world of computing, supercomputers still suffer from low resource utilization rates. To enhance supercomputing clusters with the benefits of serverless computing, a modern cloud programming paradigm for pay-as-you-go execution of stateless functions, we present rFaaS, the first RDMA-aware Function-as-a-Service (FaaS) platform. With hot invocations and decentralized function placement, we overcome the major performance limitations of FaaS systems and provide low-latency remote invocations in multi-tenant environments. We evaluate the new serverless system through a series of microbenchmarks and show that remote functions execute with negligible performance overheads. We demonstrate how serverless computing can bring elastic resource management into MPI-based high-performance applications. Overall, our results show that MPI applications can benefit from modern cloud programming paradigms to guarantee high performance at lower resource costs.

1 INTRODUCTION

The landscape of high-performance computing is dominated by the Message-Passing Interface (MPI), a *de facto* standard distributed programming paradigm. Together with job batch scheduling [40] and multithreaded frameworks for shared-memory programming, MPI is the leading use case for clusters and supercomputers [74]. New MPI standards and implementations have brought the benefits of emerging network protocols, above all with remote direct memory access (RDMA) networks such as InfiniBand [64] and the inclusion of RDMA programming through one-sided communication [44]. Yet, the current setup does not address all of the challenges of distributed computing, and a predominant example is the ability to adapt resource allocation to changing application requirements. *Evolving* and *malleable* applications [39] achieve lower efficiency when resource allocation cannot be adjusted. These applications can consist of multiple phases with varying parallelism. Starting from MPI 2.0, applications are permitted to change the number of processes during execution. However, this feature has not been explored by many applications because of a complex setup and lack of integration with resource managers [76]. In the rigid HPC world, job schedulers and applications use only a fixed number of resources, leading to overallocation and underutilization of cores.

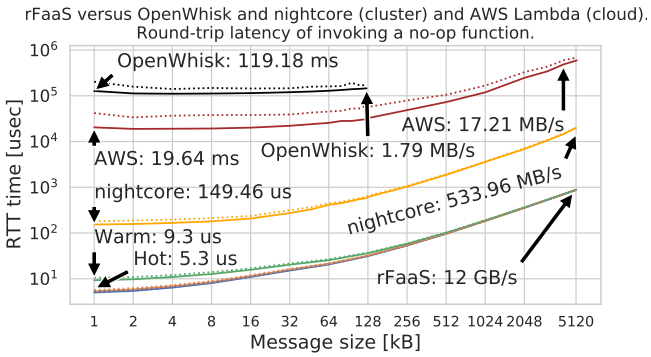
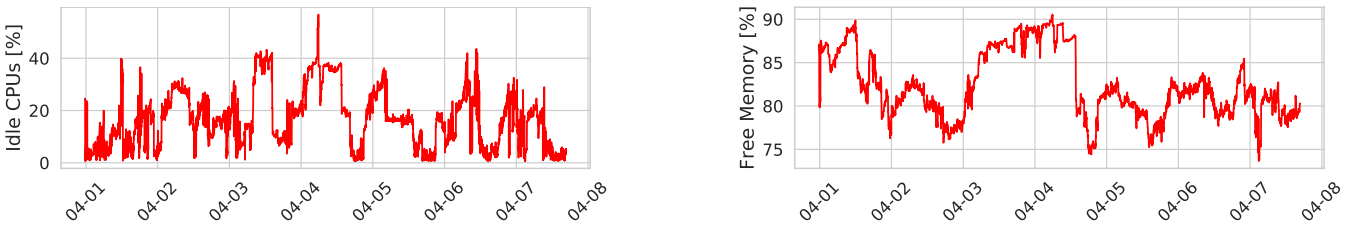


Figure 1: The remote invocations of an empty C++ function on serverless platforms and *rFaaS*: median (solid), and 99th latency (dashed) on a single worker.

Achieving high utilization rates of supercomputers has always been challenging, and past predictions showed a pessimistic research outlook: *"the goal of achieving near 100% utilization while supporting a real parallel supercomputing workload is unrealistic"* [56]. Recent results are not much more optimistic: while a usage analysis of the Kraken supercomputer capacity over a year indicates average utilization as high as 94% [87], and a median utilization of around 90% on the Mira supercomputer [73], a four-year study of the Blue Waters system capacity presents monthly utilization rates that rarely exceed 80% [57]. Furthermore, on average three-quarters of node memory is not utilized [72]. On such systems, a 10% decrease in monthly utilization rate leads to hundreds of thousands of dollars of investment into hardware that stays unused. To assess the modern scale of the problem, we analyzed over a week the utilization of the Piz Daint supercomputing system [15], and present in Figures 2a and 2b the CPU and memory utilization data, respectively. The rapid and frequent changes indicate that resources do not stay idle for an extended period of time, and this gap cannot be addressed with persistent and long-running allocations. However, fine-grained and ephemeral programming models could take advantage of such resources - to the benefit of both HPC users and administrators, as idle computing and memory resources could be offered at much lower costs. This problem is not limited to HPC and supercomputers: data centers suffer from low utilization as well, caused by resource overprovisioning to handle peak demand [60].



(a) Idle CPU cores rate (%). **(b) Free memory rate (%).**

Figure 2: Piz Daint utilization for a period of one week (31.03-7.04 in 2021): querying SLURM with a one minute interval.

In recent years, the world of computing has seen two major innovations brought by the cloud: elastic resource management and a cost decrease of 5 to 7 times [22]. Even though the early examination of cloud systems showed that Infrastructure-as-a-Service (IaaS) resources are not a viable alternative to high-performance systems, as they are characterized by significant overheads, high costs, and unsatisfactory I/O performance [51, 53, 70], their performance and attractiveness has improved over time [71, 89]. Virtual machines and containers, the important virtualization solutions in the cloud systems, have been found to be an efficient abstraction level for high-performance applications [50, 77], and cloud network performance improved as well [90, 91]. The advantages of the cloud have been quickly identified to improve the performance of on-premises clusters by allocating computing resources in the cloud [34] (*HPC plus cloud*) and executing elastic MPI applications [76] (*HPC in the cloud*). In particular, the concept of *HPC-as-a-Service* [19] brings a cloud abstraction model to manage and access HPC resources. Yet, no work has fully embraced the cloud revolution to improve the efficiency of existing supercomputing systems. The question of incorporating elastic cloud resources into MPI applications remains open due to a lack of a cloud-native programming model.

Function-as-a-Service (FaaS) is a new cloud paradigm combining the full elasticity of cloud resources with a maximally simplified programming model: users program stateless functions, and the cloud takes away the responsibility of scheduling invocations of such functions. Thanks to the fine-grained parallelism and the pay-as-you-go billing system, serverless functions have become a solution for all tasks that can benefit from an elastic allocation of computing resources. While the progress towards HPC-as-a-Service continues [23], functions are not yet ready for HPC applications due to high invocation latencies and computing costs [31, 55]. For FaaS to become a viable programming model for high-performance applications, it must overcome the crucial performance and integration challenges: (1) fully utilize the potential of network devices, (2) provide low-latency invocations with minimal added overheads, (3) offer the always-available computing resources for invocations on the critical path, (4) and integrate into existing and proven solutions for programming and dispatching high-performance software.

We address these challenges in *rFaaS*, the first **RDMA-capable serverless platform** with a decentralized resource management model (Sec. 3). We show how novel **hot** serverless invocations improve over **warm** executions with an added latency of little over 300 nanoseconds on top of the fastest available network transmission. We discuss the characteristics of HPC applications that can exploit the benefits of *rFaaS* functions (Sec. 4). We present a **programming model** for straightforward integration of *rFaaS* into new and existing C++ MPI codebases, with a high degree of compatibility with other standard-compliant frameworks. With the incorporation of serverless computing into MPI applications, we make a major step towards elastic *HPC in the cloud*. Furthermore, we provide a **batch system integration** for the dynamic allocation of serverless functions on idle resources (Sec. 5). Supercomputing systems could reasonably offer idle resources at discounted rates to incentivize better utilization. Therefore, this *HPC-as-a-Service* solution can increase the efficiency and utilization of the overall cluster. We demonstrate the elasticity, efficiency, and high performance of *rFaaS* with an evaluation on microbenchmarks and show that HPC workloads can be accelerated with serverless functions (Sec. 6).

Our paper makes the following contributions:

- We present the design and implementation of the first RDMA-capable serverless platform, including (1) a decentralized FaaS resource management protocol and (2) a novel, low-latency, and zero-copy *hot* type of serverless invocations. *rFaaS* is publicly available on an open-source license[1].
- We conduct an experimental verification against state-of-the-art open-source and commercial serverless platforms summarized in Figure 1 and show that *rFaaS* (1) has a median overhead over pure RDMA transmission of little over 300 nanoseconds, (2) achieves the available link bandwidth, and (3) scales efficiently up to 64 invocations on two nodes.
- We design a C++ programming model and an integration into cluster management systems to invoke *rFaaS* functions on spare cluster capacity. We show that we can improve supercomputers' utilization by applying modern cloud abstractions to take advantage of short-lived idle resources.
- We show how *rFaaS* can be used in an HPC context by accelerating MPI applications. With three case studies, we show that speedups up to 2.2x can be achieved through task offloading into cheap remote functions.

2 BACKGROUND

2.1 FaaS Computing

Function-as-a-service (FaaS) is a cloud service concerned with executing stateless and short-running functions. The serverless functions are dynamically allocated in the cloud, and the users are freed

[1]The code is available under the link https://github.com/spcl/rFaaS/

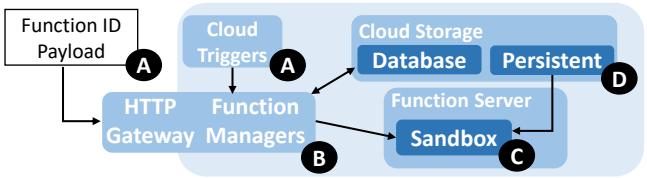


Figure 3: A high-level view on FaaS architecture.

from the usual responsibilities of managing resources. The cloud provider charges users only for the time and resources used in a function execution, and applications with irregular or infrequent workloads can benefit from the elastic allocation of computing resources and the pay-as-you-go billing system. For a cloud operator, the fine-grained executions provide an opportunity to increase system efficiency through oversubscription and more efficient scheduling. Serverless is adopted by major cloud systems [1, 3–5].

We characterize the serverless platforms briefly with a high-level overview presented in Figure 3 and refer interested readers to a wider discussion in the literature [31, 55, 86]. Functions are invoked via *triggers* (Ⓐ), including internal cloud events such as database update or a new entry in a queue, and the standard external trigger via a cloud HTTP gateway that exposes functions to the outside world. A function scheduler (Ⓑ) places the invocation in a cloud-native execution environment (Ⓒ), and the function code is downloaded from the cloud storage (Ⓓ). Function are allowed to initiate connections to external cloud resources and services, and can also use the filesystem of its sandbox as a temporary storage. A sandbox instance handles many consecutive invocations, so resources are cached and reused across executions.

Invocations. The primary types are *cold* and *warm*. *Cold* invocations occur if the FaaS manager cannot find an idle sandbox for a given function, and must allocate a new one. The latency includes the time to allocate a sandbox, download the function code from external storage and start an executor process. In a *warm* invocation, the function payload is sent directly to the executing process.

The unpredictable and high-latency cold startups are a major issues with serverless [67, 81] as they can add seconds of overhead to each invocation. Modern lightweight virtual machines are designed to support low-latency and burstable serverless invocations [20]. However, even warm invocations can incur significant overheads. On AWS Lambda, each invocation is processed by a dedicated management service to decide function placement [20]. The function input is limited to a few megabytes, so users must transmit larger payloads via the high-latency public cloud storage. The invocation's critical path is even longer in OpenWhisk [2], as it includes a controller, database, load balancer, and a message bus [78].

High-Performance Serverless. Serverless is used by compute-intensive workloads such as data analytics, video encoding, linear algebra, and machine learning [25, 41, 42, 52, 65, 69, 75, 79]. The elastic parallelism of FaaS has so far not gained significant attention in the world of HPC applications. Such applications require low-latency communication and optimized data movement. They cannot tolerate the large overheads of invoking remote functions. They need a pricing model that is fair towards compute-intensive

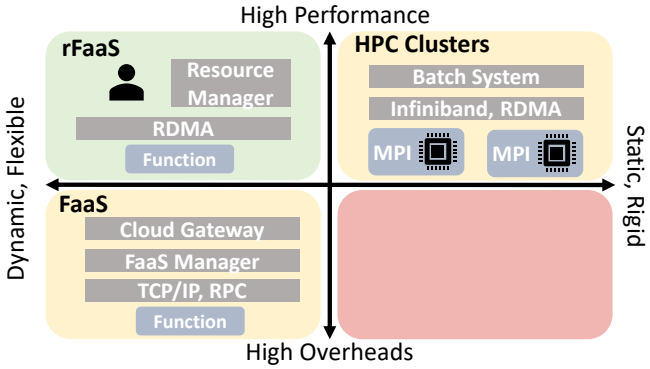


Figure 4: Comparison of execution systems for HPC: *rFaaS* offers the dynamic resource management of FaaS and performance comparable to batch systems from HPC clusters.

functions [55]. Although recent research focuses on improving the performance of serverless functions by exploiting data locality and co-locating invocations on the same machine [21], HPC applications need fast remote invocations to achieve high scalability.

3 RDMA-BASED SERVERLESS PLATFORM

In this section, we describe *rFaaS* and its most important features.

rFaaS is a serverless platform tailored for the needs of high-performance applications, combining the flexibility of FaaS systems with the low overhead executions offered by cluster systems (Figure 4). *rFaaS* implements the main FaaS paradigm of remote executions of stateless functions but avoids major performance overheads of serverless computing by replacing the REST and RPC-based invocation interface with direct memory operations on remote servers.

Our philosophy in implementing *rFaaS* is to drastically reduce the critical path of warm and cold invocations. We achieve this goal by reducing the number of parties involved in transmitting function data and removing the centralized gateway and resource manager from the invocation path. Figure 5 shows an overview of *rFaaS*: a decentralized allocation system where clients negotiate a lease of computing resources from a frequently refreshed list of available servers (Sec. 3.2). Our functions gain a direct RDMA connection to executor servers without sacrificing their *serverless* nature: no assumptions are made about the underlying computing and storage hardware as in other FaaS platforms. We capitalize on this gain further by implementing an RDMA-based invocation system designed to minimize invocation latency (Sec. 3.3).

3.1 Components of *rFaaS*

Resource Manager. A global database of active resources is a necessary component of each serverless platform. Servers become available for function execution as soon as the database contains an entry with a description of their resources and connection details (❶). The role of the resource manager is to update and distribute a ranked list of executor servers. The cluster batch system adds and removes servers, and the manager uses heartbeats to verify the status of executor servers periodically and remove unresponsive

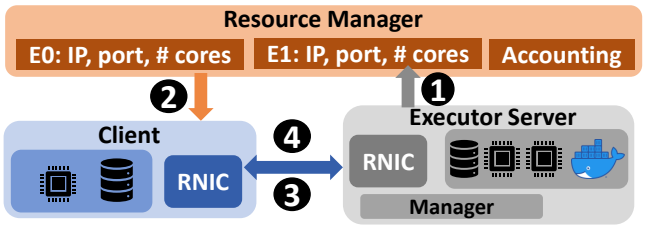


Figure 5: *rFaaS* system: resource manager receives (❶) and distributes (❷) computing resource availability, clients allocate executors (❸) and remotely invoke functions (❹).

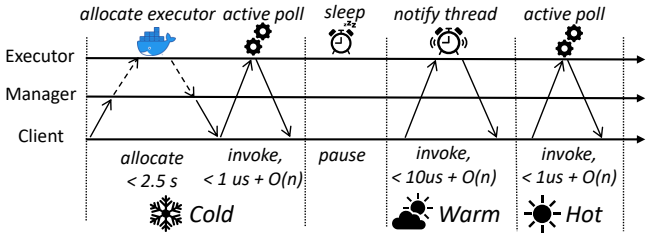


Figure 6: Lifetime of an *rFaaS* function. Similarly to serverless systems, the cold start times are dominated by sandbox initialization. Warm and hot invocation times include *rFaaS* overhead and latency of RDMA write of N bytes of payload.

resources. Clients can read the list of executor servers and receive updates asynchronously through RDMA operations (❷).

Function Executor Server. When clients begin offloading serverless tasks to *rFaaS*, they select executor servers to achieve the desired number of parallel workers. These servers offer the idle and unused hardware resources (CPU cores, memory) to support dynamic execution of serverless functions. Clients negotiate an allocation of computing resources with an executor manager (❸). The dedicated executor manager process is responsible for connecting new clients, initializing containerized executors, removing containers that are idle for a long time or exceed specified time limits, and accounting for resource consumption. When an allocation is successful, executor managers initialize an isolated execution context with an RDMA-capable execution process. Finally, clients can establish a direct RDMA connection with each allocated executor process and invoke functions by writing function header and payload directly into their memory (❹). The results are returned to the client in a similar fashion, and the allocation status is cached on the client's side for consecutive invocations on warmed-up resources.

3.2 Decentralized Allocation

A feature *rFaaS* provides is decentralized resource management, differentiating it from other commercial and open-source FaaS implementations. To execute a function, clients do not involve the resource manager. Instead, they select a permutation of resource servers and send allocation requests directly to those servers. Clients use a random permutation of a sorted list of servers to decrease the likelihood of contention and conflicts, and ensure that each server is requested exactly once. Upon successful allocation, managers allocate isolated execution contexts, initialize RDMA-aware execution processes, and notify clients. At that point, clients can send function invocations. Connections to executor processes are cached locally by clients to provide fast consecutive executions on warmed-up resources. To support a straightforward deallocation of temporary and on-demand executors, clients use the connection status to check if the execution context is alive.

3.3 Low-Latency Invocation

A critical feature of *rFaaS* is ensuring invocations have a low-latency invocation. While an on-demand allocation of idle resources improves the economics of cluster batch systems, without low-latency invocations it would be counterproductive to incorporate *rFaaS* functions into HPC applications. In Figure 6, we present the steps and overheads of various invocation models in *rFaaS*. Our platform preserves the FaaS semantics of, and we extend the invocation models with a new type of *hot* invocation that guarantees zero-copy executions on always ready and available hardware.

We now detail the characteristics of cold, warm and hot invocations, as well as the mechanisms offered to enable parallel function invocation and ensure fault tolerant execution. We then describe how the performance of invocations can be modeled.

Cold. The *cold* invocation includes significant overheads caused by the initialization of an execution context. In *rFaaS*, clients negotiate the allocation directly with executor servers by sending requests specifying the desired number of cores, memory, and timeout for the allocation. Clients send allocation requests iteratively until they succeed in allocating the desired number of computing resources. A failed allocation request is returned immediately to the client.

Executor servers initialize an isolated execution sandbox and assign the requested computing and memory resources to it. The executor process starts in the sandbox, accesses the selected RDMA device, registers memory buffers, creates worker threads pinned to assigned cores. Each executor has a configurable number of thread workers that work independently of each other, and each one corresponds to a single function instance. Clients can allocate multiple workers in a single allocation request. When the initialization is done, the client receives the executor's connection settings, establishes connections to all threads, and can write requests directly to the workers. This process leads to a *warm* or *hot* invocation, depending on the delay between allocation and the execution. Overall, sandbox initialization adds on average 25 ms and 2.7 seconds of overhead for bare-metal and Docker-based executor, respectively, on an HPC node (Section 6). The overheads of forking and initializing a new executor dominates the cold invocation time.

Warm. Warm invocations occur when a sandbox and execution process is already allocated. A client transmits the function payload to a worker thread of the execution process using a direct RDMA connection. We implement warm invocations in *rFaaS* with the help of RDMA completion events. Threads do not share RDMA resources, and they wait independently for completion events corresponding to new invocation requests. Once a completion event arrives, the thread wakes and executes the request. Handling RDMA completion events impacts performance, but significantly decreases the pressure on computing resources compared to active poll methods.

Compared to native RDMA performance, warm invocations have an overall overhead of less than 6 microseconds for a round-trip invocation. The thread enters the *hot* invocation mode immediately after execution and polls RDMA events without sleeping to improve consecutive invocations' performance. We roll back to *warm* execution after a predefined time without seeing a new invocation.

Hot. The novel *hot* invocations further improve the performance of *warm* FaaS executions by adding the new obligation that threads actively poll for invocation requests. Thread workers switch from blocking on completion queues to active polling of them. Switching to polling mode decreases the invocation latency since threads do not enter a blocked state to wait for an interrupt generated by the RDMA driver. This configuration decreases the overall overhead for a round-trip invocation to ca. 300 nanoseconds on average.

3.4 Scalability

A high-performance serverless platform must handle scaling in three domains: number of active allocations in an HPC system (users of *rFaaS*), size of each allocation (number of MPI ranks offloading work), and the number of functions invoked by each process.

Horizontal Scaling. The number of *rFaaS* clients in a system can reach many thousands with jobs using serverless acceleration on all of their MPI processes. To scale with the demand, we offer two strategies: replication and connection optimization. First, to support the many rFaaS clients in the system, we replicate the resource manager where each replica serves data on executor availability. The replicated datastores employ expensive, strongly consistent transactions to prevent stale reads in distributed settings. However, stale reads are not a concern for the replicated resource manager. A stale announcement of new resources can lead to a slightly smaller availability of computing resources for a subset of clients and only for a short time. Similarly, removing resources from the manager is not a problem since *rFaaS* clients must tolerate the volatility of transient resources. As a result, our replicated resource manager can implement a less expensive but scalable eventual consistency [84], subject to stale reads but guaranteing that all replicas eventually have the same view on the available computing resources.

Second, we optimize the connection structure of resource managers to support efficient notifications. Between resource and execution managers, we use reliable RDMA connections, as they need to support atomic operations. The updates in executor availability must be distributed to thousands of clients, but the network throughput of RDMA connections decreases significantly with the number of clients [28, 58]. Reliability is not strictly needed to distribute delta updates, and packet losses are infrequent [58]. Therefore, we can use unreliable datagrams and multicast for that task as it scales much better than RDMA connections.

Executor Scaling. Thanks to the decentralized allocation policy and a random selection, the executor managers are expected to usually receive requests only from a small fraction of potential clients. However, when the HPC cluster achieves almost ideal utilization, the list of available computing resources becomes very small. As a result, significant contention can appear when a large number of clients start a random walk over a small list of *rFaaS* executor servers. To prevent clients from overwhelming executor managers, the managers notify a selected resource manager as soon as they are fully allocated. The resource manager distributes the information to replicas and clients, and executor servers will not receive new requests until they announce availability again. Resource starvation can thus be detected much quicker, and contention can be avoided.

Parallel Invocations. *rFaaS* implements parallel functions invocations by simultaneous dispatching of many function execution requests to threads of remote executors. Since a client has a direct RDMA connection to each thread worker, it can invoke functions independently. The scalability is achieved by exploiting the non-blocking nature of RDMA write operations and using disjoint memory buffers to store invocation results. The use of multiple RDMA connections improves network utilization as more processing units of a network controller are involved [58]. Thread workers execute functions in parallel without interfering with each other. In addition, each executor thread is accounted separately and switches between hot-warm invocations on its own, further aiding elasticity.

3.5 Fault tolerance

rFaaS clients can experience failures in two ways: when the server is removed from the pool of active executors or is shut down uncontrollably, and when the function crashes the execution process. The client library caches connections for further invocations so a server disappearance will be detected through a disrupted RDMA connection, and will be removed from the local cache. Handling function failures requires the the executor manager. The manager frequently verifies the status of the executor process. When it detects that the process exited prematurely, it notifies the client of the failure. The user-side library repeats the invocation on other servers for a number of retries, to avoid infinite invocations of broken functions.

Finite Resources. Cloud services provide the illusion of infinite resources, and thanks to the large scale, serverless platforms can guarantee a Service Level Agreement (SLA) of 99.95% (AWS [9], Azure [8], Google [14]). On the other hand, *rFaaS* is an example of *opportunistic computing*, and its range of operations is limited to the spare capacity of an HPC cluster - requests beyond the available hardware cannot be fulfilled. A failed allocation process can be repeated after a user-defined wait time, with exponential backoff time. This process decreases the contention on executors, but does not guarantee resource availability: repeated backoffs might never succeed when the cluster is close to full utilization.

We extend the fault tolerance for resource exhaustion through the internal allocation of executors that are private to the MPI job. This benefits applications that cannot accomodate sudden exhaustion of resources, due to emerging load imbalance. In distributed applications, processes that succeeded allocating *public* executors in *rFaaS*, offer compute capacity to others by launching a *private* executor. These *private* executors provide an option for the processes without serverless allocations to offload a part of their workload internally and distribute tasks equally across all workers. Contrary to cloud-based FaaS platforms that acquire new resources, *rFaaS* clients still use the same hardware. Speedup is thus achieved even when without enough remote resources for the entire application.

3.6 Isolation

In addition to bare-metal executors, we include containerized executors to ensure privacy and security in the multi-tenant execution in *rFaaS*. The main requirements imposed by *rFaaS* are virtualization support for RDMA-capable network controllers and negligible performance overheads. The current implementation uses Docker containers to implement isolated execution contexts for user functions. Use of Docker in HPC systems has raised security concerns, as the Docker daemon should not be accessible to non-trusted users [16], this is not a concern in *rFaaS*: the containers are launched by the executor manager, and users never have neither control nor access to the daemon. We limit the user's code from accessing any resources, data, and code not provided with the invocation. We use the Single Root I/O Virtualization (SR-IOV) for the virtualization of network controllers in a multi-tenant environment. Virtual network functions provide isolated but high-performance access for different users [36]. Software implementations for virtualization come at the cost of non-negligible overheads and increased CPU usage [6, 61].

In principle, other solutions could be used: HPC-optimized containers such as Singularity [62] and Shifter [43], and microVMs such as Firecracker [7, 20] that provide a higher level of isolation with negligible performance overheads. To integrate other sandboxes with *rFaaS*, virtualization or passthrough to the RDMA NIC must be provided, and new instances can be launched on-demand without interacting with the batch system.

3.7 *rFaaS* versus FaaS

While *rFaaS* implements the essential semantics of FaaS computing - remote invocations on transient and multi-tenant resources with pay-as-you-go billing - we tailor the design of the serverless platform to the HPC world. The trigger mechanism is replaced with decentralized allocations and direct connection to an executor, removing the proxies and caching the connection for subsequent invocations. While serverless platforms deploy function code from storage when instantiating a sandbox, the *rFaaS* client sends the code directly to memory, removing the latencies of external storage and sandbox I/O operations from the critical path.

rFaaS is a fundamental building block for fast and cheap invocations on idle resources. We do not provide a universal solution for resource starvation, as different applications require alternative approaches. Applications with tasking, fine-grained parallelism, and load imbalance can benefit from *rFaaS* even if not all workers succeed in resource allocations. On top of the standardized interface of *rFaaS*, additional features can be implemented according to the needs of specific programming frameworks: native datatypes and serialization, collective operations, logging of invocations. Similarly, *rFaaS* does not come with a dedicated authorization system, as this adds overhead and can be provided through the HPC batch systems.

4 rFaaS APPLICATION TARGETS

rFaaS can provide significant performance boosts to applications. The guiding principle — the application never waits for remote invocations to finish — is achieved by dividing the work such that the round trip time of invocations and the time they are executed are hidden by local work. Fine-grained invocations allow developers

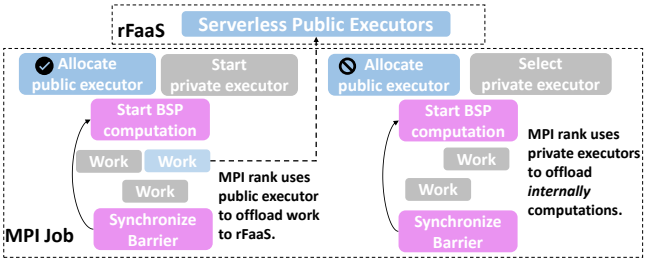


Figure 7: *rFaaS* for bulk synchronous programs: speedup without load imbalance even on limited resources.

many opportunities to accelerate their applications. Consequently, the low-latency invocations are critical for such tasks, and latency plays a part in deciding what can be safely offloaded to *rFaaS*.

We use an analytical model to estimate the overheads of *warm* and *hot* invocations in *rFaaS*, based on prior work of *LogP* [33] and *LogfP* [48] models. The network performance is expressed with parameters such as latency, CPU overhead on the sender and receiver, and gap factor. By learning the network parameters, estimating the remote function execution time, and measuring the *rFaaS* overheads (Section 6), we model the round-trip invocation time.

We design a model to decide *when* remote invocations can be integrated into HPC applications, then show *how* to use *rFaaS* as an accelerator for HPC problems. We provide examples of applications and benchmarks that are either a natural fit or can be adapted to use *rFaaS* to offload some of their work. This list is not exhaustive but provides an intuition on using *rFaaS* efficiently in practice.

Massively parallel applications. These applications are extremely malleable and can therefore make efficient use of *rFaaS*. A solver for the Black-Scholes equation [45] is a good example, as it generates many independent tasks of comparable runtime. Assuming we want to achieve the best possible performance, we measure the runtime of one task T_{local} and then compare this to the runtime T_{inv} of one invocation using *rFaaS*, to which we add the round-trip network time L. There exists a number N_{local} of tasks such that:

$$N_{local} \cdot T_{local} \geq T_{inv} + L \tag{1}$$

Therefore, if the number of tasks is greater than N_{local}, up to N_{remote} tasks can be safely computed using *rFaaS* without incurring any waiting time. N_{remote} is determined as the number of tasks necessary to saturate the available bandwidth B: $\frac{B}{Data_{inv}}$. Therefore, the throughput of the system only depends on the network link bandwidth, and the amount of work available to *rFaaS*.

Task-based applications with no sharing within tasks. Task-based applications are programs that consist of a series of tasks that must be executed, where some tasks can depend on the results of others, inducing a task dependency graph [80] - basically a graph stating the order in which tasks must be executed. Task-based applications can profit from *rFaaS*, as Eq. 1 still holds in this case. However, the number of tasks that can be offloaded at any time depends on the width of the task dependency graph at that time - the wider the graph, the more parallelism is exposed, and therefore more tasks can be transferred to *rFaaS*. As an example, we consider the prefix scan in electron microscopy image registration [29]. The width of

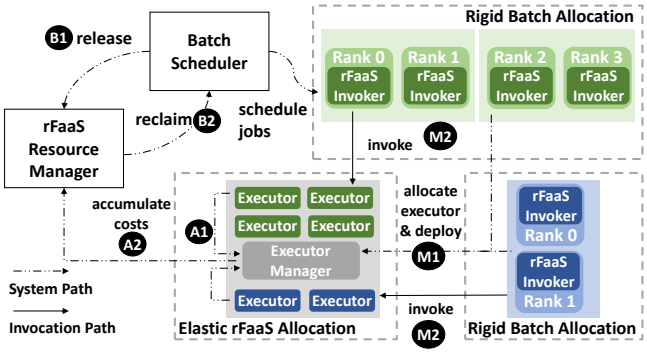


Figure 8: The system model of *HPC-as-a-Service*: *rFaaS* functions integrated with MPI applications (Ⓜ), running on batch-managed clusters (Ⓑ) with dedicated accounting (Ⓐ).

the task graph in a distributed scan varies significantly between program phases, affecting the parallel efficiency. The dispatch of tasks expands parallel resources only when needed and limits the static resource allocation to the most efficient configuration.

Hybrid BSP Applications. A common occurrence in HPC are applications that use MPI and a shared-memory parallel programming framework, e.g., OpenMP, and we propose to boost the performance of such programs using *rFaaS*. We assume a bulk synchronous execution at the MPI level: each rank performs mostly the same type of computation. In this case, we consider candidates for remote invocations OpenMP parallel loops or task constructs with no shared accesses. By applying Eq. 1, we can determine how many loop iterations or tasks can be safely offloaded without incurring waiting times. Even if a small number of iterations or tasks are solved remotely, this can still amount to significant computational effort in total, as each MPI process performs the same amount of work.

Since *rFaaS* has finite resources, the application must handle the case of *resource starvation*. While this is an application-specific problem, we provide a general principle of resource-aware serverless acceleration for BSP programs presented in Figure 7. In addition to *public* executors offered by the *rFaaS* service, MPI processes run *private* executors that allow for job-internal offloading. Thanks to the rigid structure of bulk synchronous computations, MPI ranks can mutually exchange their acceleration status before entering computational loops and find acceleration partners offering private executors. This technique allows to load-balance by distributing the workload across the entire MPI application with a single, consistent interface of serverless functions. Thus, load-balancing is possible even in case of full saturation and unequal resource availability.

5 rFaaS as HPC-as-a-Service

To enable true *HPC-as-a-Service* through serverless computing, the functions must easily integrate with existing parallel applications and cluster management systems. They should not add a significant burden on administrators when deploying the new, dynamic and flexible computing platform and accounting system. To that end, we present an integration model of *rFaaS* into the MPI-centric world of supercomputers (Figure 8). To enable native and straightforward

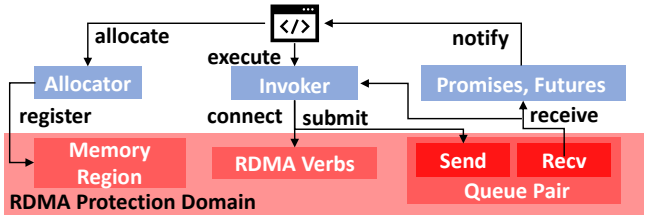


Figure 9: The *rFaaS* programming model. The model is inspired by C++ standarization efforts on the *executor* concept.

```
void compute(int size, rfaas::invoker & invoker) {
① auto alloc = invoker.allocator<double>{};
  // Automatically expanded with function's header
② rfaas::buffer<double> in = alloc.input(2 * size);
  rfaas::buffer<double> out = alloc.output(2 * size);
  // Offload part of the computation to rFaaS
③ auto f = invoker.submit("step2", in, size, out);
  // Local part of computation
  step2(in.data() + size, out.data() + size, size);
④ f.get();
⑤ invoker.deallocate(); // Release computing resources.
⑥ step3(out.data(), 2 * size);
}
void init(...) {
  MPI_Init(...);
  rfaas::invoker invoker{opts.rnic_device};
  // Pre-allocate resources for immediate invocations.
⑦ invoker.allocate(opts.lib, opts.size * sizeof(double),
    rfaas::invoker::ALWAYS_WARM_INVOCATIONS
  );
}
```

Listing 1: Example of an rFaaS-accelerated MPI application.

integration of fast serverless functions with high-performance applications, we design a C++ programming model for a high degree of compatibility with other tasking systems (Sec. 5.1). *rFaaS* is not only a standalone serverless platform — it is designed as a pluggable component into existing cluster configurations (Sec. 5.3), and provides a simple yet effective accounting procedure (Sec. 5.4).

5.1 Programming Model

To design the programming interface for *rFaaS*, we take inspiration from recent developments in C++ standard for parallel and asynchronous *executors* [13]. The prior work executors and their implementations proved that this concept is an efficient interface for dispatching tasks to accelerator devices [30, 46]. The programming model presented in Figure 9 hides the complexity of RDMA verbs under a lightweight C++ abstraction. It can be easily integrated into existing parallel applications as presented in Listing 1, and it can be adapted in the future to full compatibility with C++.

Allocator. The *allocator* (①) provides memory allocation for RDMA-enabled memory buffers and encapsulates the memory region reserved for function header (②). The allocator can be integrated effortlessly to serialize standard containers such as *std::vector* and *std::array*, and the class ensures that all memory buffers are page-aligned to achieve the highest bandwidth on RDMA [59].

Invoker. The client's *invoker* implements the submission of remote function invocations (③). It also manages RDMA connections

to remote executors and implements the allocation and deallocation of computing resources. The status of the computation can be queried with busy polling of the RDMA completion queue (④), providing the lowest latency at the cost of additional CPU time.

In addition to blocking invocations, we use the `std::future` to represent the result of unfinished executions. Users can query the status of each invocation, wait for their completions, and access the result later. Internally, the library runs a single thread that waits for RDMA work completion events and modifies a promise associated with a future when the corresponding invocation finishes. While completion events have a higher latency than active polling [66], the thread can to sleep while waiting, reducing CPU consumption.

MPI Integration. *rFaaS* programming model integrates natively with MPI applications. Each MPI process manages the remote function placements independently, as shown in Figure 8. Even if a large MPI run attempts to allocate resources simultaneously (M1), the contention is avoided by randomly selecting computing resources.

The allocation of *rFaaS* functions can be performed ahead of time (⑦) to hide the cold invocation latencies since warm executor threads are sleeping and not incurring major charges. Remote resources can be allocated and deallocated as needed (⑤), adjusting to the varying parallelism of different phases of an MPI application. With the abstractions for work submission and memory management, *rFaaS* interface can be used by modifying only those parts of the application that benefit from its elastic parallelism (⑥).

5.2 Function Deployment

As a serverless solution, *rFaaS* supports execution of arbitrary stateless functions, and similarly to the *function apps* offered by Azure Functions [3], *rFaaS* enables execution of different functions in the same execution process. However, unlike other serverless platforms, we do not rely on external storage to provide function code during allocation, as it adds significant overhead and makes on-the-fly code updates difficult. Instead, in *rFaaS* the function code is written to executor memory during the *cold* initialization process (M1). The user selects a shared library submitted to the remote invocation. Both sides query and sort the library's exported symbols, and during invocation, only the relative function index is submitted.

Listing 2 presents the standard function interface in *rFaaS*. Each thread allocates the memory regions and notifies the client about the address and access key for function's input. To invoke the function (M2), its input is written to the provided remote buffer, and the immediate value contains a invocation identifier and a function index. Each invocation includes the `size` argument specifying the actual number of bytes written by the invoker. The function returns the number of bytes in the output array that will be sent back to the client. The input buffer contains a twelve-byte header containing the address and access key for a buffer on the client's side, and the executor writes the output directly to the client's memory using an RDMA write. Thus, users gain the flexibility to invoke functions that return results into different memory regions. The immediate value of the return write contains the execution status and the invocation identifier. The latter allows the client's library to immediately identify which execution has just finished.

```
uint32_t foo(void* in, uint32_t in_size, void* out) {
  uint32_t in_len = in_size / sizeof(double);
  double* input = reinterpret_cast<double*>(in);
  double* output = reinterpret_cast<double*>(out);
  // Application can be dispatched as shared library
  uint32_t out_len = solve(input, in_len, output);
  // Return value defines the output size
  return sizeof(double) * out_len;
}
```

Listing 2: rFaaS function interface.

The library can include general-purpose static variables to store data between invocations, similarly to a sandbox's temporary filesystem. It is the user's responsibility to ensure that functions preserve their stateless nature while accessing a shared resource. Additional data can be made available to the executor through a high-performance filesystem such as Lustre [85].

5.3 Batch Systems

Efficient utilization of idle cluster resources requires two basic functionalities from a serverless platform: a release of nodes for FaaS processing with an immediate announcement to all users, and a single-step removal of executors from the serverless resource pool. *rFaaS* implements those requirements in a simple interface designed for integration with cluster job management systems.

Resource release. The batch system offers unused CPU cores for the execution of short-running serverless functions. To that end, the global resource manager offers a single REST API call to register new resources (B1). The node information is sent to the resource manager, the manager adds the server to the list of resources, and publishes updates to all registered clients through RDMA operations. Thus, *rFaaS* users become aware of the newly available computing location in a microsecond-scale latency. This is required to support efficient allocations on spare capacity that can be available only for a very short period of time (Figure 2).

Resource retrieval. Idle nodes cannot be used as FaaS executors without a safe and low-latency abort functionality. Otherwise, the resources might not be freed efficiently for batch jobs with higher priority. Batch systems use REST API to sent *remove* call with a parameter describing the allowed time for resource deallocation (B2). When the request is immediate (no further computing time is allowed), all active functions invocations are aborted, *termination* replies are sent to clients through existing RDMA channels, and the final billing update is sent to the resource manager. Otherwise, active invocations might be permitted to finish the computation if their remaining compute time is lower than the permitted time limit. No further invocations will be granted while the batch system retrieves resources and active connections are gracefully terminated.

5.4 Accounting

The pricing of *rFaaS* is presented in the equation below, and it includes two basic cost components: allocation of cluster resources C_a, and active computation time C_c.

$$C = C_a \cdot t_a + C_c \cdot t_c$$

The total allocation t_a measured in GB-second is calculated across all executors as a product of allocation time and memory requested. Whereas the total active computation time t_c measured in seconds

represents the total time all remote workers are busy with computations. Costs C_a and C_c are measured in $ per GB-second and $ per second, respectively, and represent the total cost of occupying and actively using system resources (i.e., cores, memory) for a given period of time. The pricing system of *rFaaS* is similar to traditional FaaS systems for provisioned function invocations [12], where clients are charged for pre-allocation of cloud resources. However, unlike traditional FaaS, *rFaaS* does not charge for invocation calls , only charging for active computation time. As a result, clients of *rFaaS* only pay C_c for actual computation,not including times when remote executor threads sleep due to warm invocations.

On HPC systems, we propose that these elastic resources should be offered at a significant discount. This can ensure better utilization rates while not impacting the ability to schedule classical jobs, and acknowledging they do not offer the same guarantees of availability.

The accounting procedure is implemented in a global database associated with the resource manager (A2). The manager exposes memory regions for RDMA atomic *fetch-and-add* operations, providing executor managers with an RDMA-native way of accumulating cost results without consuming CPU resources. Similarly, executors use atomic operations to report billing updates to their local manager (A2). We accumulate charges with a granularity of one second, and billing data is updated after accumulating new charges larger than the granularity threshold. This avoids a loss of accounting data due to abrupt termination of *rFaaS* executor instances. Contention of atomic operations is not an issue, as cost accumulation is never on the critical path of function invocation.

6 rFaaS IN PRACTICE

To demonstrate the fitness for purpose of *rFaaS* for HPC, we answer critical questions in the form of extensive evaluation.

(1) Is *rFaaS* fast enough for HPC?
(2) Are the overheads for initialization prohibitively large?
(3) Does *rFaaS* scale with larger messages?
(4) Does *rFaaS* scale with more workers?
(5) Does *rFaaS* improve performance for a typical HPC task?
(6) Are very short *rFaaS* functions usable in HPC computations?
(7) Is *rFaaS* performance competetive against OpenMP?

Platform. For the purpose of this evaluation, we deploy *rFaaS* in a local cluster and execute benchmark code on 4 nodes, each with two 18-core Intel(R) Xeon(R) Gold 6154 CPU @ 3.00GHz and 377 GB of memory. Nodes are equipped with Mellanox MT27800 Family NIC with a 100 Gb/s Single-Port link that is configured with RoCEv2 support. Nodes communicate with each other via a switch, and we measured an RTT latency of 3.69 μs and a bandwidth of 11,686.4 MiB/s. We use Docker 20.10.5 with executor image `ubuntu:20.04`, and we use the Mellanox's SR-IOV plugin to run containers over virtual device functions, Our software is implemented in C++, using g++ 8.3.1, and OpenMPI 4.0.5.

6.1 Invocation Latency

We begin with the most important characteristic for *rFaaS*: the latency of invoking a remote function. We measure hot and warm invocations of a non-op function with the same input and output size. We use a warmed-up, single-threaded, bare-metal executor

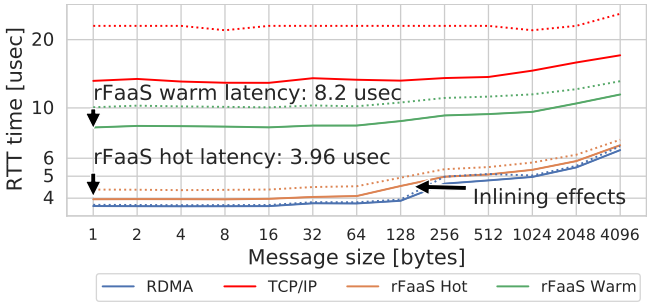


Figure 10: The RTT of an no-op *rFaaS* function and network transport, median (solid) and 99th latency (dashed).

with the main thread pinned to a CPU core, perform 10,000 repetitions, and report the median. We compute the non-parametric 99% confidence intervals of the median [47, 63], and find that the interval bounds are very tight (<1%). To assess the overheads of *rFaaS* invocations, we measure the latency of RDMA and TCP/IP transmissions.For the former, we use *ib_write_lat* from the *perftest* package, execute it with thread pinning and warm-up iterations, and report the median. For the latter, we use *netperf* with page-aligned buffers and process pinning, and report the mean.

The results for data sizes from 1 byte to 4 kB presented in Figure 10 show that the overhead of a no-op function in *rFaaS* in a process is 326 nanoseconds on average, when compared to RDMA writes. The measurements for a Docker-based executor present aditional ca. 50 nanoseconds overhead over RDMA writes when using a container. The only exception is the message size of 128 bytes, where the overhead increases to 630 nanoseconds. There, RDMA can use message inlining for both directions of the transmission which improves the performance of small messages significantly [58]. However, the communication in *rFaaS* is asymmetrical: we transmit 12 bytes more for the input. The maximal supported inlining size is 128 bytes on our device, forcing *rFaaS* to use non-inlined write operations for one direction. The average overhead of a warm execution is 4.67 microseconds. Here, the containerization adds a measurable performance overhead, and Docker-based warm executions have an additional overhead of ca. 650 nanoseconds.

With slightly more than 300 nanoseconds of overhead, *rFaaS* enables remote function invocation with no noticeable performance penalty, conclusively answering: ***rFaaS* is fast enough for HPC**.

6.2 Cold Invocation Overheads

Figures 11a and 11b present the overhead of a single *cold* invocation on a bare-metal and Docker-based executor, respectively. The data comes from 1000 invocations with a single no-op C++ function, compiled into a shared library of size 7,88 kB. In all tested configurations, the longest step is the creation of workers. All other steps: the connection establishment to the manager, submitting an allocation and code, and code invocation, take single-digit milliseconds to accomplish. We can therefore claim that *rFaaS* does not introduce significant overheads apart from the sandbox initialization.

While the current version of Docker shows an overhead of approximately 2.7 seconds to spawn workers, approaches such as

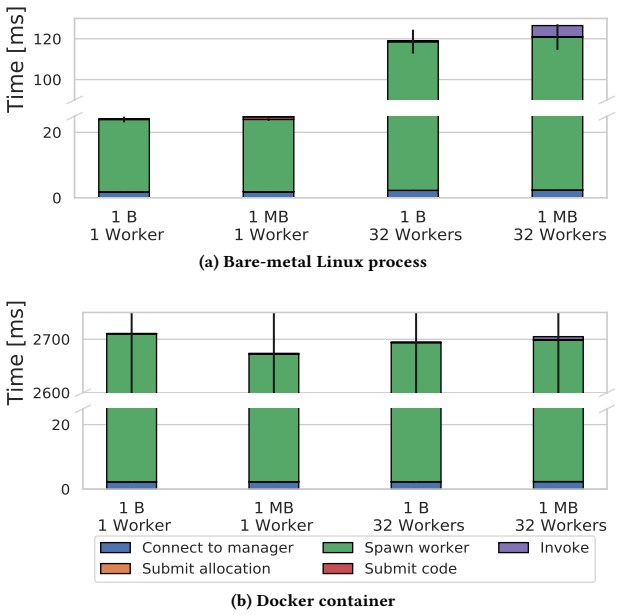


Figure 11: Cold invocations of *rFaaS* functions.

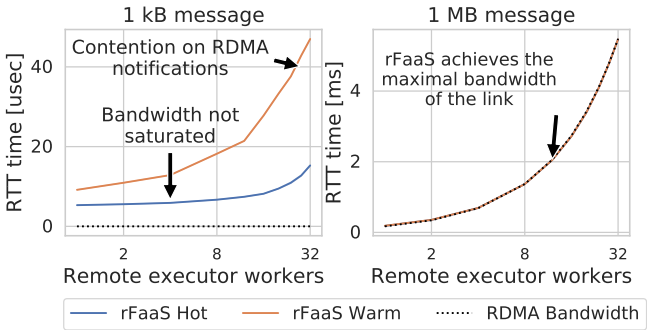


Figure 12: *rFaaS* invocations on parallel executors.

Firecracker [7] exist, that reduce this time to as little as 125 milliseconds. Firecracker cannot currently deploy on HPC systems, but the developers are working towards expanding its capabilities.

The initialization time of MPI takes between 0.8 and 3 seconds for 32 processes depending on the MPI library used [88] — comparable to the *rFaaS* overhead of cold initialization. Developers can overcome this overhead by initializing *rFaaS* like calling *MPI_Init()*, and the nonblocking nature of this process should allow *rFaaS* workers to be ready to by the time MPI completes its own initialization.

We therefore claim that **cold invocation overheads of *rFaaS* do not pose an obstacle for the use in HPC**.

6.3 Scalability with payload size.

To compare the performance of *rFaaS* and serverless platforms, we evaluate a non-op C++ function that returns the provided input on a payload range from 1 kB to 5 MB. Since other platforms cannot accept raw memory data, we generate a base64-encoded string that approximately matches the input size used in *rFaaS*.

We compare against AWS Lambda [1], a state-of-the-art commercial FaaS solution, OpenWhisk [2], an open-source FaaS platform, nightcore [54], a low-latency serverless platform. In Lambda, we deploy a native function implemented using the official C++ Runtime [11], we expose an HTTP endpoint with no authorization, and run the experiment in an AWS *t2.micro* VM instance in the same region as the function. We deploy on the cluster a standalone OpenWhisk using Docker with Kafka and API gateway [10]. A C++ function in OpenWhisk is invoked as a regular application, accepting inputs no larger than 125 kB through *argc* and *argv*. We deploy a *nightcore* instance on the cluster with a non-op C++ function.

We present the evaluation result in Figure 1. On all payload sizes, *rFaaS* clearly provides significantly better performance. *rFaaS* invocations are between 695x and 3,692x faster than AWS Lambda executions, thanks to the performance attainable with a low-latency network and the native support for transmitting raw data that suits high-performance applications very well. *rFaaS* is between 17x and 28x times faster than nightcore, another FaaS platform with microsecond-scale latencies. Similarly, *rFaaS* provides a speedup between 5,904x and 22,406x when compared to OpenWhisk.

Therefore, we answer that *rFaaS* provides significant performance improvements over contemporary FaaS platforms and ***rFaaS* scales well with message size**.

6.4 Scalability with parallel workers.

To verify that RDMA-capable functions scale efficiently to handle integration into scalable applications, we place managers on 36-core CPUs and evaluate the overheads associated with parallel invocations. We execute the no-op function on warmed-up, bare-metal executors having allocated from 1 to 32 worker threads.

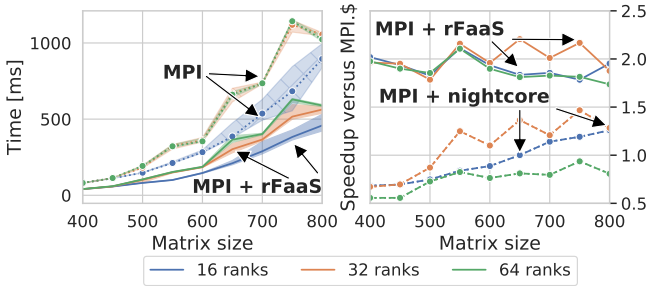
Figure 12 presents the round-trip latencies for invoking functions with 1 kB and 1MB payloads, respectively. The overhead of handling many concurrent connections is insignificant on hot invocations with a smaller payload. While the Docker executor shows performance increase (hot) and decrease (warm) on the 1 kB payload, the difference on 1MB payload is less than 1%. However, execution times increase significantly with the number of workers when sending 1 MB data, due to saturating network capacity (100 Gb/s). This shows that *rFaaS* scaling is limited only by the available bandwidth.

Therefore, we claim that **parallel scaling of *rFaaS* executors is bounded only by network capacity**.

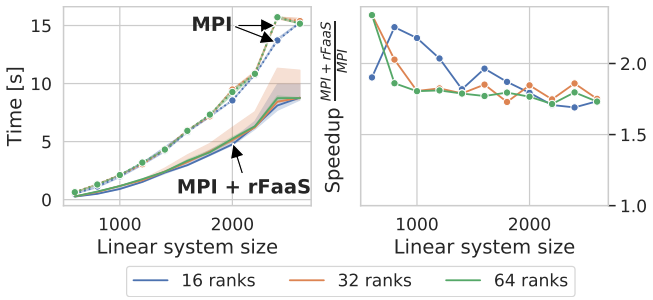
6.5 Use-case: matrix-matrix multiplication

To learn how much performance can be gained by offloading complex tasks to the spare capacity of HPC clusters, we use a matrix-matrix multiplication kernel as a stand-in for compute-intensive tasks in general, and compare the performance of a traditional MPI application with an *elastic* one that uses *rFaaS* acceleration.

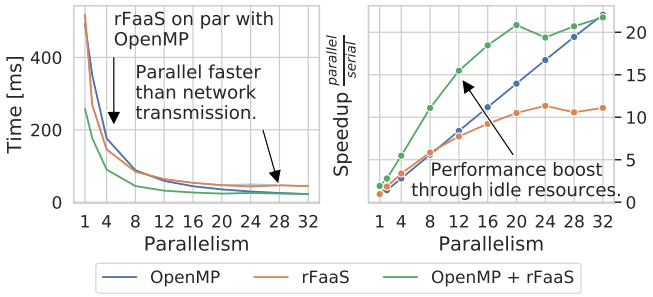
We run an *MPI* application where each rank performs a matrix-matrix multiplication, averages it over 100 repetitions, and we measure the median kernel time across MPI ranks. MPI ranks are distributed across two 36-core nodes, and we pin each rank to a single core. Then, we deploy an *MPI + rFaaS* application where each rank



(a) Matrix-matrix multiplication: *MPI* (dashed) and *MPI+*rFaaS (solid).



(b) Jacobi method, 100 iterations: *MPI* (dashed) and *MPI+*rFaaS (solid).



(c) Black-Scholes from PARSEC 3.0, 10 million equations: *OpenMP*, rFaaS.

Figure 13: *rFaaS* in practice, reported medians with non-parametric 95% CIs.

allocates a single bare-metal *rFaaS* function. *rFaaS* executors are deployed on two other 36-core nodes, and with such concentration of MPI and *rFaaS* computing resources, we show that sharing the network bandwidth does not prevent efficient serverless acceleration. Because of a high computation to communication ratio, we split workload equally, and both MPI rank and the function compute half of the result matrix. For a matrix size N, each invocation accepts two matrices with N^2 elements each, performs $\frac{2N^3}{2}$ floating-point operations, and returns a matrix with N^2 elements.

Figure 13a shows *rFaaS* provides a speedup between 1.88x and 1.94x depending on the number of MPI processes. This speedup is consistent as we vary the size of the multiplied matrices. We implemented the same function on the nightcore FaaS platform. As functions there accept only JSON arguments, we serialize matrices with C++ libraries [17, 18]. We deployed two instances with a fixed number of 32 function instances, and performed the same evaluation. The *MPI + nightcore* achieves worse speedup due to the overhead of serialization, and lower utilization of network bandwidth. Functions with a good ratio of computation to unique memory accesses can be accelerated with *rFaaS*. As long as this condition holds, ***rFaaS* improves the performance of HPC workloads**.

6.6 Use-case: linear solver

To show a serverless acceleration of a BSP-style problem, we consider the Jacobi linear solver, where a part of each iteration is offloaded to *rFaaS*. For a linear system of size $N \times N$, we perform approximately $2N^2$ floating-point operations in each iteration. The function receives in total $2N + N^2$ elements of the system matrix, right-hand vector, and the current solution approximation. With an equal split of workload, the function traverses half of the system and returns $\frac{N}{2}$ elements. The $O(N^2)$ order of both communication and computation would require offloading a small fraction of the work to balance computation and communication. Instead, we perform a classical serverless optimization of caching resources in a warmed-up sandbox. Since the matrix and right-hand vector do not change between iterations, we submit them only for the first invocation. As long as the allocated function is not removed, we send only an updated solution vector in consequent iterations.

We evaluate the approach in the same setting as matrix multiplication (Section 6.5), with MPI ranks averaging Jacobi method with 1000 iterations over ten repetitions. Figure 13b demonstrates a speedup between 1.7 and 2.2 when *rFaaS* acceleration is used. Since each iteration takes just between 1 and 15 milliseconds, results must be returned with a minimal overhead to offer performance comparable with the main MPI process: **the low-latency invocations in *rFaaS* apply to millisecond-scale computations.**

6.7 Use-case: Black-Scholes

We show how *rFaaS* can accelerate a pure OpenMP application, using the Black-Scholes solver [45] from the PARSEC suite [24]. Black-Scholes solves the same partial differential equation for different parameters, and we dispatch independent equations to bare-metal parallel executors. We evaluate the benchmark on *native* input with approximately 229 MB of input and 38 MB of output and present the results in Figure 13c. We show that offloading the entire work to *rFaaS* scales efficiently compared to OpenMP, as long as the workload per thread is not close to the network transmission time of approximately 30 ms. We achieve further speedup by enhancing the OpenMP application with offloading half of the work to the same number of parallel workers on idle HPC resources. ***rFaaS* offers scalable parallelism bounded by network performance only.**

7 RELATED WORK

High-performance FaaS. FuncX [27] is a federated and distributed FaaS platform designed to bring serverless function abstraction to scientific computing. Nonetheless, FuncX does not take advantage of HPC networks and implements an hierarchical and centralized design, that has long invocation paths between clients and remote workers. As a result, even warm invocations take at least 90ms. Nightcore [54] is a FaaS runtime that offers microsecond-scale

warm invocations. Nightcore introduces the concept of internal function calls — invocations made by a running function. As a result, these internal function calls do not require inter-node communication and are satisfied locally. SAND [21] is a serverless platform optimized for workflows of serverless functions through grouping of functions and dedicated message buses for subsequent invocatons. In contrast, *rFaaS* explots co-location via explicit parallelism of executor allocation, and optimizes invocation latencies through RDMA communication. Archipelago [82] and Wukong [26] allow users to submit jobs that are represented as a directed acyclic graph (DAG) of functions. They perform latency-aware scheduling of a submitted DAGs: Wukong uses a decentralized and dynamic scheduling built on top of AWS Lambda, while Archipelago focuses on resource partitioning for decentralized schedulers and optimizing the control plane of a serverless platform. In contrast, *rFaaS* provides an HPC-centered FaaS platform where both allocation and invocation are decentralized and optimized with a direct client - worker connection. Application-layer solutions such as Wukong, and optimization strategies such as sandbox warming up in Archipelago, can be ported to *rFaaS* as well.

Elastic MPI. Raveendran et al. [76] proposed a framework for MPI programs that adapts to the elasticity of the cloud by restarting applications with different numbers of processes. Martin et al. [68] presented Flex-MPI, an automatic reconfiguration framework for malleable MPI applications. Huang et al. [49] presented Adaptive MPI, an MPI implementation in Charm++ with virtualization and reconfiguration. Other adaptive MPI solutions focus on checkpointing and migration [32, 37, 38]. In contrast, *rFaaS* concentrates on the dynamic acceleration of MPI programs with resources allocated on-the-fly, and it requires neither restarting nor reconfiguration of the MPI program to incorporate new parallel resources. *rFaaS* functions can be executed on transient resources that are available only for a short time. SR-IOV is a virtualization solution that offers high performance [35], it cannot however use idle resources elastically without guarantees of availability in the way *rFaaS* can.

Active messages. Our approach shares similar goals with Active Messages proposed by Eicken [83]: fully utilize available network performance by reducing operating system overheads and providing direct access to network devices. While Active Messages are a form of Remote Procedure Calls and optimize message-passing applications by running asynchronously short functions on the destination, *rFaaS* implements the serverless semantics of invoking functions on dynamically allocated and abstracted executors. Furthermore, we enable general-purpose computing on multi-tenant executor servers, as AM do not consider node sharing between clients with different functions, and we allow for elastic resource usage thanks to the pay-as-you-go billing system.

8 CONCLUSIONS

This work is the first to show that FaaS computing, the new cloud model of stateless function invocations on dynamically allocated resources, can be enhanced with low-latency network protocols such as RDMA. We introduced hot serverless functions, a new invocation type that expands the guarantees of warm serverless functions with always-ready computing resources. We presented an integration of our serverless platform with MPI and batch processing, the de facto standard use patterns of supercomputers, to prove that high performance can be achieved with elastic resource management.

We conducted an exhaustive evaluation of RDMA-capable functions and demonstrated invocations with less than one microsecond of overhead, efficient parallel scalability, and processing latencies significantly lower than other FaaS platforms.

Overall, our results show that HPC applications can benefit from modern cloud programming paradigms to guarantee high performance at lower resource costs.

ACKNOWLEDGMENTS

This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 programme (grant agreement EPIGRAM-HS, No. 801039, and grant agreement RED-SEA, No. 955776), and from the Schweizerische Nationalfonds zur Förderung der wissenschaftlichen Forschung (SNF, Swiss National Science Foundation) through Project 170415. We would also like to thank the Swiss National Supercomputing Centre (CSCS) for providing us with access to their supercomputing machines Daint and Ault.

REFERENCES

[1] 2014. AWS Lambda. https://aws.amazon.com/lambda/. Accessed: 2020-01-20.
[2] 2016. Apache OpenWhisk. https://openwhisk.apache.org/. Accessed: 2020-01-20.
[3] 2016. Azure Functions. https://azure.microsoft.com/en-us/services/functions/. Accessed: 2020-01-20.
[4] 2016. IBM Cloud Functions. https://cloud.ibm.com/functions/. Accessed: 2020-01-20.
[5] 2017. Google Cloud Functions. https://cloud.google.com/functions/. Accessed: 2020-01-20.
[6] 2017. The Linux SoftRoCE Driver. https://www.youtube.com/watch?v=NumH5YeVjHU. Accessed: 2021-03-24.
[7] 2018. Firecracker. https://github.com/firecracker-microvm/firecracker. Accessed: 2020-01-20.
[8] 2018. SLA for Azure functions. https://azure.microsoft.com/en-gb/support/legal/sla/functions/v1_1/. Accessed: 2021-05-25.
[9] 2019. AWS Lambda Service Level Agreement. https://aws.amazon.com/lambda/sla/. Accessed: 2021-05-25.
[10] 2020. Apache OpenWhisk standalone Docker image. https://hub.docker.com/r/openwhisk/standalone. Accessed: 2021-04-09.
[11] 2020. AWS Lambda C++ Runtime. https://github.com/awslabs/aws-lambda-cpp. Accessed: 2020-01-20.
[12] 2020. AWS Lambda Pricing. https://aws.amazon.com/lambda/pricing/. Accessed: 2020-08-20.
[13] 2020. P0443R14: A Unified Executors Proposal for C++. https://wg21.link/p0443r14. Online; accessed 11.03.2021.
[14] 2021. Cloud Functions Service Level Agreement (SLA). https://cloud.google.com/functions/sla. Accessed: 2021-05-25.
[15] 2021. Piz Daint. https://www.cscs.ch/computers/piz-daint/. Accessed: 2020-01-20.
[16] 2021. SLURM 20.11: Containers Guide. https://slurm.schedmd.com/containers.html. Accessed: 2021-05-25.
[17] 2021. Tencet rapidjson library. https://github.com/Tencent/rapidjson. Accessed: 2021-05-31.
[18] 2021. USCiLab cereal library. https://github.com/USCiLab/cereal. Accessed: 2021-05-31.
[19] M. AbdelBaky, M. Parashar, H. Kim, K. E. Jordan, V. Sachdeva, J. Sexton, H. Jamjoom, Z. Shae, G. Pencheva, R. Tavakoli, and M. F. Wheeler. 2012. Enabling High-Performance Computing as a Service. *Computer* 45, 10 (2012), 72–80. https://doi.org/10.1109/MC.2012.293
[20] Alexandru Agache, Marc Brooker, Alexandra Iordache, Anthony Liguori, Rolf Neugebauer, Phil Piwonka, and Diana-Maria Popa. 2020. Firecracker: Lightweight Virtualization for Serverless Applications. In *17th USENIX Symposium on Networked Systems Design and Implementation (NSDI 20)*. USENIX Association, Santa Clara, CA, 419–434. https://www.usenix.org/conference/nsdi20/presentation/agache
[21] Istemi Ekin Akkus, Ruichuan Chen, Ivica Rimac, Manuel Stein, Klaus Satzke, Andre Beck, Paarijaat Aditya, and Volker Hilt. 2018. SAND: Towards High-Performance Serverless Computing. In *Proceedings of the 2018 USENIX Conference*

on Usenix Annual Technical Conference (Boston, MA, USA) *(USENIX ATC '18)*. USENIX Association, USA, 923–935.

[22] Michael Armbrust, Armando Fox, Rean Griffith, Anthony D. Joseph, Randy H. Katz, Andrew Konwinski, Gunho Lee, David A. Patterson, Ariel Rabkin, and Matei Zaharia. 2009. *Above the Clouds: A Berkeley View of Cloud Computing*. Technical Report. EECS Department, University of California, Berkeley.

[23] Mary Baker, Tom Coughlin, Paolo Faraboschi, Eitan Frachtenberg, Kim Keeton, Danny Lange, Phil Laplante, Andrea Matwyshyn, Avi Mendelson, Cecilia Metra, Dejan Milojicic, and Roberto Saracco. 2021. *Technology Predictions 2021*. Technical Report. IEEE Computer Society.

[24] Christian Bienia, Sanjeev Kumar, Jaswinder Pal Singh, and Kai Li. 2008. The PARSEC Benchmark Suite: Characterization and Architectural Implications. In *Proceedings of the 17th International Conference on Parallel Architectures and Compilation Techniques* (Toronto, Ontario, Canada) *(PACT '08)*. Association for Computing Machinery, New York, NY, USA, 72–81. https://doi.org/10.1145/1454115.1454128

[25] Joao Carreira, Pedro Fonseca, Alexey Tumanov, Andrew Zhang, and Randy Katz. 2019. Cirrus: A Serverless Framework for End-to-End ML Workflows. In *Proceedings of the ACM Symposium on Cloud Computing* (Santa Cruz, CA, USA) *(SoCC '19)*. Association for Computing Machinery, New York, NY, USA, 13–24. https://doi.org/10.1145/3357223.3362711

[26] Benjamin Carver, Jingyuan Zhang, Ao Wang, Ali Anwar, Panruo Wu, and Yue Cheng. 2020. Wukong: A Scalable and Locality-Enhanced Framework for Serverless Parallel Computing. In *Proceedings of the 11th ACM Symposium on Cloud Computing* (Virtual Event, USA) *(SoCC '20)*. Association for Computing Machinery, New York, NY, USA, 1–15. https://doi.org/10.1145/3419111.3421286

[27] Ryan Chard, Yadu Babuji, Zhuozhao Li, Tyler Skluzacek, Anna Woodard, Ben Blaiszik, Ian Foster, and Kyle Chard. 2020. FuncX: A Federated Function Serving Fabric for Science. In *Proceedings of the 29th International Symposium on High-Performance Parallel and Distributed Computing* (Stockholm, Sweden) *(HPDC '20)*. Association for Computing Machinery, New York, NY, USA, 65–76. https://doi.org/10.1145/3369583.3392683

[28] Youmin Chen, Youyou Lu, and Jiwu Shu. 2019. Scalable RDMA RPC on Reliable Connection with Efficient Resource Sharing. In *Proceedings of the Fourteenth EuroSys Conference 2019* (Dresden, Germany) *(EuroSys '19)*. Association for Computing Machinery, New York, NY, USA, Article 19, 14 pages. https://doi.org/10.1145/3302424.3303968

[29] Marcin Copik, Tobias Grosser, Torsten Hoefler, Paolo Bientinesi, and Benjamin Berkels. 2020. Work-stealing prefix scan: Addressing load imbalance in large-scale image registration. arXiv:2010.12478 [cs.DC]

[30] Marcin Copik and Hartmut Kaiser. 2017. Using SYCL as an Implementation Framework for HPX.Compute. In *Proceedings of the 5th International Workshop on OpenCL* (Toronto, Canada) *(IWOCL 2017)*. Association for Computing Machinery, New York, NY, USA, Article 30, 7 pages. https://doi.org/10.1145/3078155.3078187

[31] Marcin Copik, Grzegorz Kwasniewski, Maciej Besta, Michal Podstawski, and Torsten Hoefler. 2020. SeBS: A Serverless Benchmark Suite for Function-as-a-Service Computing. arXiv:2012.14132 [cs.DC]

[32] Iván Cores, Patricia González, Emmanuel Jeannot, María J. Martín, and Gabriel Rodríguez. 2017. An Application-Level Solution for the Dynamic Reconfiguration of MPI Applications. In *High Performance Computing for Computational Science – VECPAR 2016*, Inês Dutra, Rui Camacho, Jorge Barbosa, and Osni Marques (Eds.). Springer International Publishing, Cham, 191–205.

[33] David Culler, Richard Karp, David Patterson, Abhijit Sahay, Klaus Erik Schauser, Eunice Santos, Ramesh Subramonian, and Thorsten von Eicken. 1993. LogP: Towards a Realistic Model of Parallel Computation. In *Proceedings of the Fourth ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming* (San Diego, California, USA) *(PPOPP '93)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/155332.155333

[34] Marcos Dias de Assuncao, Alexandre di Costanzo, and Rajkumar Buyya. 2009. Evaluating the Cost-Benefit of Using Cloud Computing to Extend the Capacity of Clusters. In *Proceedings of the 18th ACM International Symposium on High Performance Distributed Computing* (Garching, Germany) *(HPDC '09)*. Association for Computing Machinery, New York, NY, USA, 141–150. https://doi.org/10.1145/1551609.1551635

[35] Tiago Pais Pitta de Lacerda Ruivo, Gerard Bernabeu Altayo, Gabriele Garzoglio, Steven Timm, Hyun Woo Kim, Seo-Young Noh, and Ioan Raicu. 2014. *Efficient High-Performance Computing with Infiniband Hardware Virtualization*. Technical Report. Technical Reports–Illinois Institute of Technology, Argonne National Laboratory.

[36] Y. Dong, X. Yang, X. Li, J. Li, K. Tian, and H. Guan. 2010. High performance network virtualization with SR-IOV. In *HPCA - 16 2010 The Sixteenth International Symposium on High-Performance Computer Architecture*. 1–10. https://doi.org/10.1109/HPCA.2010.5416637

[37] K. El Maghraoui, T. J. Desell, B. K. Szymanski, and C. A. Varela. 2007. Dynamic Malleability in Iterative MPI Applications. In *Seventh IEEE International Symposium on Cluster Computing and the Grid (CCGrid '07)*. 591–598. https://doi.org/10.1109/CCGRID.2007.45

[38] Kaoutar El Maghraoui, Boleslaw K. Szymanski, and Carlos Varela. 2006. An Architecture for Reconfigurable Iterative MPI Applications in Dynamic Environments. In *Parallel Processing and Applied Mathematics*, Roman Wyrzykowski, Jack Dongarra, Norbert Meyer, and Jerzy Waśniewski (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 258–271.

[39] Dror G. Feitelson and Larry Rudolph. 1996. Toward convergence in job schedulers for parallel supercomputers. In *Job Scheduling Strategies for Parallel Processing*, Dror G. Feitelson and Larry Rudolph (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 1–26.

[40] Dror G. Feitelson, Larry Rudolph, Uwe Schwiegelshohn, Kenneth C. Sevcik, and Parkson Wong. 1997. Theory and practice in parallel job scheduling. In *Job Scheduling Strategies for Parallel Processing*, Dror G. Feitelson and Larry Rudolph (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 1–34.

[41] L. Feng, P. Kudva, D. Da Silva, and J. Hu. 2018. Exploring Serverless Computing for Neural Network Training. In *2018 IEEE 11th International Conference on Cloud Computing (CLOUD)*. 334–341. https://doi.org/10.1109/CLOUD.2018.00049

[42] Sadjad Fouladi, Francisco Romero, Dan Iter, Qian Li, Shuvo Chatterjee, Christos Kozyrakis, Matei Zaharia, and Keith Winstein. 2019. From Laptop to Lambda: Outsourcing Everyday Jobs to Thousands of Transient Functional Containers. In *2019 USENIX Annual Technical Conference (USENIX ATC 19)*. USENIX Association, Renton, WA, 475–488. https://www.usenix.org/conference/atc19/presentation/fouladi

[43] Lisa Gerhardt, Wahid Bhimji, Shane Canon, Markus Fasel, Doug Jacobsen, Mustafa Mustafa, Jeff Porter, and Vakho Tsulaia. 2017. Shifter: Containers for HPC. *Journal of Physics: Conference Series* 898 (oct 2017), 082021. https://doi.org/10.1088/1742-6596/898/8/082021

[44] Robert Gerstenberger, Maciej Besta, and Torsten Hoefler. 2013. Enabling Highly-Scalable Remote Memory Access Programming with MPI-3 One Sided. In *Proceedings of the International Conference on High Performance Computing, Networking, Storage and Analysis* (Denver, Colorado, USA). ACM, 53:1–53:12.

[45] Alexander Heinecke, Stefanie Schraufstetter, and Hans-Joachim Bungartz. 2012. A Highly Parallel Black–Scholes Solver Based on Adaptive Sparse Grids. *Int. J. Comput. Math.* 89, 9 (June 2012), 1212–1238. https://doi.org/10.1080/00207160.2012.690865

[46] Thomas Heller, Hartmut Kaiser, Patrick Diehl, Dietmar Fey, and Marc Alexander Schweitzer. 2016. Closing the Performance Gap with Modern C++. In *High Performance Computing*, Michela Taufer, Bernd Mohr, and Julian M. Kunkel (Eds.). Springer International Publishing, Cham, 18–31.

[47] Torsten Hoefler and Roberto Belli. 2015. Scientific Benchmarking of Parallel Computing Systems: Twelve Ways to Tell the Masses When Reporting Performance Results. In *Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis* (Austin, Texas) *(SC '15)*. Association for Computing Machinery, New York, NY, USA, Article 73, 12 pages. https://doi.org/10.1145/2807591.2807644

[48] Torsten Hoefler, Torsten Mehlan, Frank Mietke, and Wolfgang Rehm. 2006. LogfP - A Model for small Messages in InfiniBand. In *Proceedings of the 20th IEEE International Parallel & Distributed Processing Symposium (IPDPS), PMEO-PDS'06 Workshop* (Rhodes, Greece).

[49] Chao Huang, Gengbin Zheng, Laxmikant Kalé, and Sameer Kumar. 2006. Performance Evaluation of Adaptive MPI. In *Proceedings of the Eleventh ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming* (New York, New York, USA) *(PPoPP '06)*. Association for Computing Machinery, New York, NY, USA, 12–21. https://doi.org/10.1145/1122971.1122976

[50] Wei Huang, Jiuxing Liu, Bulent Abali, and Dhabaleswar K. Panda. 2006. A Case for High Performance Computing with Virtual Machines. In *Proceedings of the 20th Annual International Conference on Supercomputing* (Cairns, Queensland, Australia) *(ICS '06)*. Association for Computing Machinery, New York, NY, USA, 125–134. https://doi.org/10.1145/1183401.1183421

[51] A. Iosup, S. Ostermann, M. N. Yigitbasi, R. Prodan, T. Fahringer, and D. Epema. 2011. Performance Analysis of Cloud Computing Services for Many-Tasks Scientific Computing. *IEEE Transactions on Parallel and Distributed Systems* 22, 6 (2011), 931–945. https://doi.org/10.1109/TPDS.2011.66

[52] V. Ishakian, V. Muthusamy, and A. Slominski. 2018. Serving Deep Learning Models in a Serverless Platform. In *2018 IEEE International Conference on Cloud Engineering (IC2E)*. 257–262. https://doi.org/10.1109/IC2E.2018.00052

[53] K. R. Jackson, L. Ramakrishnan, K. Muriki, S. Canon, S. Cholia, J. Shalf, H. J. Wasserman, and N. J. Wright. 2010. Performance Analysis of High Performance Computing Applications on the Amazon Web Services Cloud. In *2010 IEEE Second International Conference on Cloud Computing Technology and Science*. 159–168. https://doi.org/10.1109/CloudCom.2010.69

[54] Zhipeng Jia and Emmett Witchel. 2021. Nightcore: Efficient and Scalable Serverless Computing forLatency-Sensitive, Interactive Microservices. In *Proceedings ofthe 26th ACM International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS '21)*. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3445814.3446701

[55] Eric Jonas, Johann Schleier-Smith, Vikram Sreekanti, Chia-che Tsai, Anurag Khandelwal, Qifan Pu, Vaishaal Shankar, Joao Carreira, Karl Krauth, Neeraja Jayant Yadwadkar, Joseph E. Gonzalez, Raluca Ada Popa, Ion Stoica, and David A. Patterson.

2019. Cloud Programming Simplified: A Berkeley View on Serverless Computing. *CoRR* abs/1902.03383 (2019). arXiv:1902.03383 http://arxiv.org/abs/1902.03383

[56] James Patton Jones and Bill Nitzberg. 1999. Scheduling for Parallel Supercomputing: A Historical Perspective of Achievable Utilization. In *Job Scheduling Strategies for Parallel Processing*, Dror G. Feitelson and Larry Rudolph (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 1–16.

[57] Matthew D. Jones, Joseph P. White, Martins Innus, Robert L. DeLeon, Nikolay Simakov, Jeffrey T. Palmer, Steven M. Gallo, Thomas R. Furlani, Michael T. Showerman, Robert Brunner, Andry Kot, Gregory H. Bauer, Brett M. Bode, Jeremy Enos, and William T. Kramer. 2017. Workload Analysis of Blue Waters. *CoRR* abs/1703.00924 (2017). arXiv:1703.00924 http://arxiv.org/abs/1703.00924

[58] Anuj Kalia, Michael Kaminsky, and David G. Andersen. 2014. Using RDMA Efficiently for Key-Value Services. In *Proceedings of the 2014 ACM Conference on SIGCOMM* (Chicago, Illinois, USA) *(SIGCOMM '14)*. Association for Computing Machinery, New York, NY, USA, 295–306. https://doi.org/10.1145/2619239.2626299

[59] Anuj Kalia, Michael Kaminsky, and David G. Andersen. 2016. Design Guidelines for High Performance RDMA Systems. In *2016 USENIX Annual Technical Conference (USENIX ATC 16)*. USENIX Association, Denver, CO, 437–450. https://www.usenix.org/conference/atc16/technical-sessions/presentation/kalia

[60] K. Kambatla, V. Yarlagadda, Í. Goiri, and A. Grama. 2018. UBIS: Utilization-Aware Cluster Scheduling. In *2018 IEEE International Parallel and Distributed Processing Symposium (IPDPS)*. 358–367. https://doi.org/10.1109/IPDPS.2018.00045

[61] Daehyeok Kim, Tianlong Yu, Hongqiang Harry Liu, Yibo Zhu, Jitu Padhye, Shachar Raindel, Chuanxiong Guo, Vyas Sekar, and Srinivasan Seshan. 2019. FreeFlow: Software-based Virtual RDMA Networking for Containerized Clouds. In *16th USENIX Symposium on Networked Systems Design and Implementation (NSDI 19)*. USENIX Association, Boston, MA, 113–126. https://www.usenix.org/conference/nsdi19/presentation/kim

[62] Gregory M. Kurtzer, Vanessa Sochat, and Michael W. Bauer. 2017. Singularity: Scientific containers for mobility of compute. *PLOS ONE* 12, 5 (05 2017), 1–20. https://doi.org/10.1371/journal.pone.0177459

[63] Jean-Yves Le Boudec. 2010. *Performance evaluation of computer and communication systems*. Epfl Press.

[64] Jiuxing Liu, Jiesheng Wu, and Dhabaleswar K. Panda. 2004. High Performance RDMA-Based MPI Implementation over InfiniBand. *International Journal of Parallel Programming* 32, 3 (01 Jun 2004), 167–198. https://doi.org/10.1023/B:IJPP.0000029272.69895.c1

[65] Pedro García López, Marc Sánchez Artigas, Simon Shillaker, Peter R. Pietzuch, David Breitgand, Gil Vernik, Pierre Sutra, Tristan Tarrant, and Ana Juan Ferrer. 2019. ServerMix: Tradeoffs and Challenges of Serverless Data Analytics. *CoRR* abs/1907.11465 (2019). arXiv:1907.11465 http://arxiv.org/abs/1907.11465

[66] P. MacArthur and R. D. Russell. 2012. A Performance Study to Guide RDMA Programming Decisions. In *2012 IEEE 14th International Conference on High Performance Computing and Communication 2012 IEEE 9th International Conference on Embedded Software and Systems*. 778–785. https://doi.org/10.1109/HPCC.2012.110

[67] Johannes Manner, Martin Endreß, Tobias Heckel, and Guido Wirtz. 2018. Cold start influencing factors in function as a service. In *2018 IEEE/ACM International Conference on Utility and Cloud Computing Companion (UCC Companion)*. IEEE, 181–188.

[68] Gonzalo Martín, David E. Singh, Maria-Cristina Marinescu, and Jesús Carretero. 2015. Enhancing the performance of malleable MPI applications by using performance-aware dynamic reconfiguration. *Parallel Comput.* 46 (2015), 60–77. https://doi.org/10.1016/j.parco.2015.04.003

[69] Ingo Müller, Renato Marroquin, and Gustavo Alonso. 2019. Lambada: Interactive Data Analytics on Cold Data using Serverless Cloud Infrastructure. *ArXiv* abs/1912.00937 (2019).

[70] Jeffrey Napper and Paolo Bientinesi. 2009. Can Cloud Computing Reach the Top500?. In *Proceedings of the Combined Workshops on UnConventional High Performance Computing Workshop plus Memory Access Workshop* (Ischia, Italy) *(UCHPC-MAW '09)*. Association for Computing Machinery, New York, NY, USA, 17–20. https://doi.org/10.1145/1531666.1531671

[71] Marco A. S. Netto, Rodrigo N. Calheiros, Eduardo R. Rodrigues, Renato L. F. Cunha, and Rajkumar Buyya. 2018. HPC Cloud for Scientific and Business Applications: Taxonomy, Vision, and Research Challenges. *ACM Comput. Surv.* 51, 1, Article 8 (Jan. 2018), 29 pages. https://doi.org/10.1145/3150224

[72] Gagandeep Panwar, Da Zhang, Yihan Pang, Mai Dahshan, Nathan DeBardeleben, Binoy Ravindran, and Xun Jian. 2019. Quantifying Memory Underutilization in HPC Systems and Using It to Improve Performance via Architecture Support. In *Proceedings of the 52nd Annual IEEE/ACM International Symposium on Microarchitecture* (Columbus, OH, USA) *(MICRO '52)*. Association for Computing Machinery, New York, NY, USA, 821–835. https://doi.org/10.1145/3352460.3358267

[73] Tirthak Patel, Zhengchun Liu, Raj Kettimuthu, Paul Rich, William Allcock, and Devesh Tiwari. 2020. Job Characteristics on Large-Scale Systems: Long-Term Analysis, Quantification, and Implications. In *Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis* (Atlanta, Georgia) *(SC '20)*. IEEE Press, Article 84, 17 pages.

[74] Prakash Prabhu, Thomas B. Jablin, Arun Raman, Yun Zhang, Jialu Huang, Hanjun Kim, Nick P. Johnson, Feng Liu, Soumyadeep Ghosh, Stephen Beard, Taewook Oh, Matthew Zoufaly, David Walker, and David I. August. 2011. A Survey of the Practice of Computational Science. In *State of the Practice Reports* (Seattle, Washington) *(SC '11)*. Association for Computing Machinery, New York, NY, USA, Article 19, 12 pages. https://doi.org/10.1145/2063348.2063374

[75] Qifan Pu, Shivaram Venkataraman, and Ion Stoica. 2019. Shuffling, Fast and Slow: Scalable Analytics on Serverless Infrastructure. In *16th USENIX Symposium on Networked Systems Design and Implementation (NSDI 19)*. USENIX Association, Boston, MA, 193–206. https://www.usenix.org/conference/nsdi19/presentation/pu

[76] A. Raveendran, T. Bicer, and G. Agrawal. 2011. A Framework for Elastic Execution of Existing MPI Programs. In *2011 IEEE International Symposium on Parallel and Distributed Processing Workshops and Phd Forum*. 940–947. https://doi.org/10.1109/IPDPS.2011.240

[77] Cristian Ruiz, Emmanuel Jeanvoine, and Lucas Nussbaum. 2015. Performance Evaluation of Containers for HPC. In *Euro-Par 2015: Parallel Processing Workshops*, Sascha Hunold, Alexandru Costan, Domingo Giménez, Alexandru Iosup, Laura Ricci, María Engracia Gómez Requena, Vittorio Scarano, Ana Lucia Varbanescu, Stephen L. Scott, Stefan Lankes, Josef Weidendorfer, and Michael Alexander (Eds.). Springer International Publishing, Cham, 813–824.

[78] M. Sciabarrà. 2019. *Learning Apache OpenWhisk: Developing Open Serverless Solutions*. O'Reilly Media, Incorporated.

[79] Vaishaal Shankar, Karl Krauth, Qifan Pu, Eric Jonas, Shivaram Venkataraman, Ion Stoica, Benjamin Recht, and Jonathan Ragan-Kelley. 2018. numpywren: serverless linear algebra. *CoRR* abs/1810.09679 (2018). arXiv:1810.09679 http://arxiv.org/abs/1810.09679

[80] Sergei Shudler, Alexandru Calotoiu, Torsten Hoefler, and Felix Wolf. 2017. Isoefficiency in Practice: Configuring and Understanding the Performance of Task-Based Applications. In *Proceedings of the 22nd ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming* (Austin, Texas, USA) *(PPoPP '17)*. Association for Computing Machinery, New York, NY, USA, 131–143. https://doi.org/10.1145/3018743.3018770

[81] Paulo Silva, Daniel Fireman, and Thiago Emmanuel Pereira. 2020. Prebaking Functions to Warm the Serverless Cold Start. In *Proceedings of the 21st International Middleware Conference* (Delft, Netherlands) *(Middleware '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3423211.3425682

[82] Arjun Singhvi, Kevin Houck, Arjun Balasubramanian, Mohammed Danish Shaikh, Shivaram Venkataraman, and Aditya Akella. 2019. Archipelago: A Scalable Low-Latency Serverless Platform. arXiv:1911.09849 [cs.DC]

[83] T. v. Eicken, D. E. Culler, S. C. Goldstein, and K. E. Schauser. 1992. Active Messages: A Mechanism for Integrated Communication and Computation. In *[1992] Proceedings the 19th Annual International Symposium on Computer Architecture*. 256–266. https://doi.org/10.1109/ISCA.1992.753322

[84] Werner Vogels. 2009. Eventually Consistent. *Commun. ACM* 52, 1 (Jan. 2009), 40–44. https://doi.org/10.1145/1435417.1435432

[85] Feiyi Wang, Sarp Oral, Galen Shipman, Oleg Drokin, Tom Wang, and Isaac Huang. 2009. Understanding lustre filesystem internals. *Oak Ridge National Laboratory, National Center for Computational Sciences, Tech. Rep* (2009).

[86] Liang Wang, Mengyuan Li, Yinqian Zhang, Thomas Ristenpart, and Michael Swift. 2018. Peeking behind the Curtains of Serverless Platforms. In *Proceedings of the 2018 USENIX Conference on Usenix Annual Technical Conference* (Boston, MA, USA) *(USENIX ATC '18)*. USENIX Association, USA, 133–145.

[87] Haihang You and Hao Zhang. 2013. Comprehensive Workload Analysis and Modeling of a Petascale Supercomputer. In *Job Scheduling Strategies for Parallel Processing*, Walfredo Cirne, Narayan Desai, Eitan Frachtenberg, and Uwe Schwiegelshohn (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 253–271.

[88] Weikuan Yu, Jiesheng Wu, and Dhabaleswar K. Panda. 2005. Fast and Scalable Startup of MPI Programs in InfiniBand Clusters. In *High Performance Computing - HiPC 2004*, Luc Bougé and Viktor K. Prasanna (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 440–449.

[89] Y. Zhai, M. Liu, J. Zhai, X. Ma, and W. Chen. 2011. Cloud versus in-house cluster: Evaluating Amazon cluster compute instances for running MPI applications. In *SC '11: Proceedings of 2011 International Conference for High Performance Computing, Networking, Storage and Analysis*. 1–10.

[90] J. Zhang, X. Lu, and D. K. Panda. 2016. High Performance MPI Library for Container-Based HPC Cloud on InfiniBand Clusters. In *2016 45th International Conference on Parallel Processing (ICPP)*. 268–277. https://doi.org/10.1109/ICPP.2016.38

[91] Jie Zhang, Xiaoyi Lu, and Dhabaleswar K. (DK) Panda. 2017. Designing Locality and NUMA Aware MPI Runtime for Nested Virtualization Based HPC Cloud with SR-IOV Enabled InfiniBand. *SIGPLAN Not.* 52, 7 (April 2017), 187–200. https://doi.org/10.1145/3140607.3050765