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FAABRIC: Fine-Grained Distribution of Scientific Workloads in the Cloud

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Abstract

With their high parallelism and resource needs, many scientific applications benefit from cloud deployments. Today, scientific applications are executed on dedicated pools of VMs, resulting in resource fragmentation: users pay for underutilised resources, and providers cannot reallocate unused resources between applications. While serverless cloud computing could address these issues, its programming model is incompatible with the use of shared memory and message passing in scientific applications: serverless functions do not share memory directly on the same VM or support message passing semantics when scheduling functions dynamically.

We describe FAABRIC, a new serverless cloud runtime that transparently distributes applications with shared memory and message passing across VMs. FAABRIC achieves this by scheduling computation in a fine-grained (thread/process) fashion through a new execution abstraction called *Granules*. To support shared memory, Granules are isolated using WebAssembly but share memory directly; to support message passing, Granules offer asynchronous point-to-point communication. FAABRIC schedules Granules to meet an application's parallelism needs. It also synchronises changes to Granule's shared memory, and migrates Granules to improve locality.

1 Introduction

Cloud computing offers on-demand access to plentiful resources, making it an attractive choice for highly-parallel scientific applications in hydrodynamics [44], genomics [7], and epidemiology [28]. Such applications often employ parallel programming models that use multi-threading with *shared memory* (e.g. OpenMP [45]) and distributed processing with *message passing* (e.g. MPI [40]).

Cloud providers have introduced platforms, e.g. AWS Batch [3] and Azure Batch [30], that support such workloads. These platforms typically dedicate a pool of virtual machines (VMs) to execute a queue of jobs [3, 30]. This allows such platforms to support shared memory and message passing applications: the provider schedules jobs on one or more VMs according to the requested parallelism (e.g. MPI's world size or OpenMP's `OMP_NUM_THREADS`). Shared memory applications are normally executed on a single VM with many CPU cores and large memory sizes.

Deploying scientific applications on a fixed set of VMs, however, leads to resource fragmentation: if a job does not use all available resources or cannot be bin-packed onto available VMs, users pay for idle or under-utilised VMs; providers also cannot exploit a user's idle resources, diminishing the efficiency of their infrastructure [3, 30].

To achieve higher utilisation, serverless computing [4, 13, 32] distributes workloads as fine-grained *functions*, which execute on large VM clusters, isolated through lightweight mechanisms (e.g. containers [43], micro-VMs [1, 4], or WebAssembly [15, 60]). Serverless computing thus reduces underutilisation by distributing workloads at a fine granularity across machines [4, 13, 32]. By making more fine-grained decisions about how to allocate each VM's resources, a provider achieves higher utilisation and thus lower per-tenant costs.

The programming models used in scientific applications, namely shared memory and message passing [23], make it challenging to support such applications in serverless environments: (1) *shared memory* applications rely on threads for parallelism, requiring state to be shared: threads must access the same address space, which is not possible among serverless functions running in different containers, potentially on different VMs. In addition, when deployed in a serverless setting, multi-threaded code is restricted to the parallelism available within a function's isolation boundary, e.g. a single container; and (2) *message passing* applications need a fixed-size pool of stateful processes to support consistent synchronous communication – this is unavailable in a serverless setting, in which functions tend to be short-lived, stateless and only communicate through storage [17].

We describe **FAABRIC**, a new serverless cloud runtime that executes scientific applications with shared memory and message passing. For this, FAABRIC exploits the new abstraction of *Granules*, which allow for thread- and process-granular scheduling. FAABRIC does not require changes to existing parallel programming models: it transparently executes ap-

plications that use OpenMP API [45] for shared memory or MPI API [40] for message passing. It achieves this through the following contributions:

(1) Supporting multi-threading/processing via Granules. FAABRIC executes applications as batches of distributed *Granules* (§3.1) running on shared VMs. A Granule can share memory with other Granules to offer thread semantics, or have private memory for process semantics. Granules can be spawned (or migrated) based on a *snapshot* taken from a parent Granule. FAABRIC uses WebAssembly [16] to isolate Granules and take snapshots of a Granule's state: its shared/private memory, message queues, address information and execution state, e.g. stack pointers and function tables.

(2) Transparent distribution of Granules. FAABRIC allows the provider to distribute computation using Granules. A scheduler in FAABRIC can choose to spawn or migrate Granules across VM. It makes scheduling decisions when Granules reach *control points*, which are triggered by system calls and calls to parallel APIs. At each control point, FAABRIC may spawn new Granules to add a logical thread or process to the application, increasing parallelism; or migrate existing Granules, e.g. to increase locality of execution.

(3) Distributed synchronisation of address spaces. To support shared memory programming, FAABRIC must offer sequential consistency within each Granule, provide distributed synchronisation primitives, e.g. mutexes and barriers, and synchronise distributed writes to shared address spaces (§4). Granules synchronise writes to the address space by building lists of *byte-wise diffs*. Each Granule maintains a record of writes to shared memory pages, performs byte-wise comparisons against its parent snapshot and propagates changes back to a main Granule via byte-wise diffs. To support updates to shared variables across Granules, byte-wise diff specify a *merge* operation, e.g. summation over shared variables.

(4) Asynchronous messaging through Granule groups. To support message passing between Granules, FAABRIC organises them into *Granule groups*. Each Granule is assigned an index within the group and can send/receive messages to/from Granules in the group. FAABRIC maintains a set of queues for each Granule to buffer incoming messages, thus sending/receiving messages asynchronously without the need for Granules to have been scheduled. This prevents message loss during Granule migration. FAABRIC implements common collective communication operations, such as all-reduce [41]. Its implementation uses fast in-memory message exchange between co-located Granules on the same VM.

In our evaluation, we use FAABRIC to execute scientific applications implemented using OpenMP and MPI (LAMMPS [55], and the ParRes kernels [48]) and compare them to native OpenMP and OpenMPI. When executing a queue of 100 applications on a 32 VM cluster, FAABRIC can reduce makespan by up to 23% thanks to its granular scheduling of threads and processes.

Domain	Name	Language	SM	MP
Molecular dynamics	LAMMPS [54]	C++	✗	✓
	MDAnalysis [29]	Python	✓	✗
Bio-informatics	BioPython [9]	Python	✓	✗
	gatk [10]	Java	✓	✗
Fluid dynamics	OpenFOAM [44]	C++	✗	✓
	SU2 [62]	C++	✓	✗
Deep learning	OpenCV [42]	C++	✗	✓
	Tensorflow [63]	Python	✓	✗

Table 1: Github's most-starred projects in scientific domains use shared memory (SM) or message passing (MP)

2 Scientific Applications in Cloud

Next, we outline the benefits and challenges associated with using cloud models for scientific applications (§2.1). We then analyse what support representative APIs for shared memory and message passing require from their execution environment (§2.2). Based on this, we develop a list of features necessary to deploy such applications in serverless cloud (§2.3).

2.1 Cloud models for scientific applications

Cloud platforms for scientific applications such as AWS Batch [3] and Azure Batch [30] allocate a dedicated pool of VMs to execute jobs. Each VM has the same size, as determined by the number of vCPUs and memory in GB. For general purpose VMs, memory increases linearly with vCPUs and price per hour [33]. Jobs in a queue are assigned VMs [38] based on their requested parallelism. For example, MPI jobs specify the number of processes through the command line: `mpirun -np <num_processes>` and are assigned enough VMs such that the sum of vCPUs is greater or equal to the requested processes.

This introduces efficiency challenges due to fragmentation: if a job does not use all of its assigned resources, these resources are wasted. For example, the number of MPI process requested may not be a multiple of the number of vCPUs per VM. In addition, different jobs cannot execute concurrently on the same VM [34]. In all of these cases, users pay for under-utilised or idle resources, and providers cannot allocate these resources to other jobs in the queue.

Reducing the VM size reduces fragmentation but impacts performance: message passing jobs become less co-located, and shared memory jobs have less available memory. Allocating a mix of different VM sizes in the pool only partially alleviates these problems, because the resource requirements of jobs are unknown ahead of time, making it challenging for providers to provide the right distribution of VM sizes.

In response, cloud platforms have increasingly adopted fine-grained distribution to reduce costs for users, and increase infrastructure utilisation [6, 19]. This has culminated in today's serverless cloud offerings, such as AWS Lambda [4] and Azure Functions [32], in which providers take full control of the parallelism and distribution of applications, billing users to a millisecond granularity [17].

Serverless applications are divided into thousands of

```
int[] weights = initWeights();

for (int i = 0; i < numSteps; i++) {
#pragma omp parallel shared(weights) {
    int threadNum = omp_get_thread_num();
    int nThreads = omp_get_num_threads();
    updateWeights(weights, threadNum, nThreads);
#pragma omp single
    applyWeights(weights);
}
```

Listing 1: Pseudocode for machine learning training using OpenMP's `parallel` abstraction (Within the `parallel` block, the OpenMP runtime controls the degree of parallelism, and ensures access to and synchronisation of the shared variable `weights`.)

small stateless tasks, which can be parallelised and distributed [4, 13, 32]. This gives providers the flexibility to allocate resources, and execute functions on those resources, according to bespoke policies. The finer-grained the serverless functions become, the higher the packing density that the provider can achieve and the more control a provider has over the resource allocation to each application.

2.2 Shared memory and message passing APIs

Although scientific applications cover diverse domains, many employ the same two programming models: shared memory and message passing. Shared memory is used for parallelism within a single machine, e.g. using multi-threading libraries such as OpenMP [45]; and message passing is used for parallelism across machines, e.g. using MPI [40] and multiprocessing. Tab. 1 shows the most starred open-source repositories in several scientific application domains on Github, which all use either or both of these programming models.

OpenMP and MPI, along with other parallel programming models, offer high-level declarative APIs that impose certain features on the underlying execution environment. If we want to deploy such applications with fine-grained distribution in a serverless cloud environment, the cloud platform must offer support to parallelise the computation, and partition, distribute and synchronise private and shared data.

Listing 1 shows a sample OpenMP implementation of stochastic gradient descent (SGD) [53], a core algorithm in machine learning training. The `omp parallel` construct requests that a `for` loop be executed in parallel with access to a single shared variable, the `weights` vector. The OpenMP runtime has control over the underlying threads and data partitioning between them. It must ensure read-only access to the shared address space, except for the `weights` vector, which receives synchronised writes from multiple threads.

The environment used to execute this code must spawn and execute parallel threads, each with access to a shared address space, and provide synchronisation primitives for accessing shared variables. This is trivial on a single host but becomes difficult if we distribute the computation. In a distributed environment, the shared address space must be made available and synchronised across VMs. Any coordination primitives, such as locks, must also operate in a distributed manner.

```
int worldSize, rank;
MPI_Comm_size(MPI_COMM_WORLD, &worldSize);
MPI_Comm_rank(MPI_COMM_WORLD, &rank);
int[] weights = initWeights();

for (int i = 0; i < numSteps; i++) {
  updateWeights(weights, rank, worldSize);
  MPI_Allreduce(MPI_IN_PLACE, weights, nWeights,
      MPI_INT, MPI_SUM, 0, MPI_COMM_WORLD);
  if(rank == 0) applyWeights(weights);
}
```

Listing 2: Pseudocode for machine learning traning using MPI's `MPI_Allreduce` function (The MPI runtime controls the degree of parallelism, data partitioning and messaging topology.)

Platform	Threads/ processes	Fixed parallelism	Shared addr. space	Direct comms.
AWS Batch [3]	✓	✓	✗	✓
Azure Batch [30]	✓	✓	✗	✓
Azure Dur. Funcs. [35]	✗	✓	✗	✗
AWS Step Functions [5]	✗	✓	✗	✗
AWS Lambda [4]	✗	✗	✗	✗
Azure Functions [32]	✗	✗	✗	✗
Crucial [8]	✓	✗	✗	✗
Faasm [60]	✗	✗	✓	✗
Faastlane [20]	✗	✗	✓	✗
Kappa [65]	✓	✗	✗	✓
SAND [2]	✗	✗	✗	✓
FAABRIC	✓	✓	✓	✓

Table 2: Cloud support for scientific workloads (We differentiate between batch-compute, serverless-compute and academic.)

As another example, Listing 2 shows an SGD implementation based on MPI's `MPI_Allreduce()` operation: concurrent processes execute the same function to transform and aggregate results on multiple VMs. The MPI runtime manages the processes, data transfers and messaging topology: it sums the weights and broadcasts the result to all processes.

The execution environment for this code must provide a fixed-size pool of processes, each of which maintains in-memory state, and can send/receive messages to/from the others in the group. The processes count cannot be changed throughout the application's lifetime due to the complexity of maintaining consistent in-memory process state, and preserving the rank-based addressing scheme between processes. This makes it challenging to vary the assigned resources.

2.3 Requirements

To perform fine-grained distribution of the code in Listing 1 and 2, a cloud platform must support the following features: thread/process semantics, fixed parallelism, shared address space and direct communication. Tab. 2 summarises the support for these features in today's scientific cloud platforms, and contrasts them with serverless platforms.

Thread/process semantics. When an application uses threads or processes for parallel computation, the execution environment must (i) fork and join child processes, which duplicate the parent's process state; and (ii) spawn and join threads, which share the parent's address space.

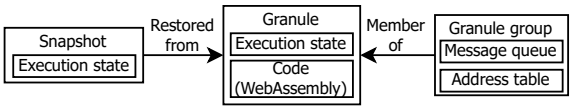


Figure 1: Key abstractions in FAABRIC (Granules are restored from snapshots, and each Granule is a member of a Granule group).

Existing scientific and serverless cloud platforms support thread/process semantics, but only *within* a given VM or serverless function. Although each VM/function can fork a process/thread, the degree of parallelism is limited by the resources allocated to the host. For example, on AWS Lambda [4], it is possible to spawn new threads but they run inside the same function, competing for the same resources. This limits the flexibility afforded to the provider, preventing them from arbitrarily distributing each thread and process on any VM, e.g. to achieve optimal bin-packing of multiple tenants.

Control of parallelism. Typically, parallel applications use a known number of threads/processes and employ synchronisation primitives (e.g. barriers, mutexes and locks) to ensure correct execution. A known parallelism degree allows applications to partition data and computation appropriately.

Existing scientific cloud platforms [3, 30] provide a fixed level of parallelism to each job. They only allocate each VM to one job, resulting in unused resources if the job does not exploit a VM's full parallelism. Serverless platforms, on the other hand, do not guarantee a fixed level of parallelism, instead allocating available resources from the shared infrastructure. While this means that serverless platforms cannot execute scientific workloads, they can perform fine-grained distribution according to their own scheduling policies. In an ideal scientific computing environment, the platform would both guarantee a fixed level of parallelism, while retaining control over its own fine-grained scheduling decisions.

Shared address space. As shown in Listing 1, multi-threaded applications assume that threads share the same virtual address space. To avoid concurrency issues, access to the address space must be coordinated. Standard libraries [26, 52] and OSs provide implementations of synchronisation primitives such as mutexes, semaphores and barriers.

As with thread/process semantics, today's cloud-based scientific and serverless platforms both support shared memory within a single VM/function. This means that shared memory parallelism is limited to the scale of a single VM/function, preventing the provider from arbitrarily distributing threads. The ideal scientific computing environment would be able to distribute threads, while maintaining a distributed shared address space across them, as well as providing distributed coordination primitives.

Direct communication. Each process in a message-passing application must be able to transfer data to other processes (see Listing 2). In MPI, this is done based on an address represented as an integer (rank).

Existing scientific cloud computing platforms support low-latency point-to-point communication for applications, as long as the available parallelism is sufficient to execute a fixed-size pool of threads. These platforms, however, cannot redistribute resources within a running application, as they cannot migrate processes between VMs. Serverless platforms isolate functions even if they belong to the same application, preventing them from obtaining stable identities for communication. An ideal scientific cloud environment would enable long-lived stateful processes with direct communication, yet allow the resources allocated for these processes to be migrated and shared between applications.

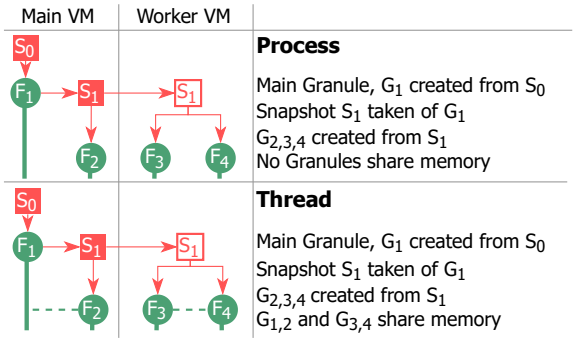


Figure 2: Thread/process semantics with Granules

3 Executing Threads and Processes

FAABRIC is a serverless cloud runtime that supports multi-threading and multi-processing, yet offers fine-grained distribution. It introduces a new parallel computing primitive, the *Granule*, with thread and process semantics (§3.1). Granules allow FAABRIC to control an application's parallelism and distribution via *control points* (§3.2). At control points, the FAABRIC runtime interrupts the application to add, remove or migrate Granules (§3.3). FAABRIC thus efficiently executes parallel applications and gives the cloud provider control over scheduling (§3.4).

3.1 Granule abstraction

To support multi-threading and multi-processing, FAABRIC uses Granules. Granules can be snapshotted and restored across VMs to support the parent/child semantics of threads and processes. They also share a single distributed address space for shared memory programming (§4). Finally, they support the direct exchange of messages within Granule groups for message passing (§5).

Fig. 1 gives an overview of the key abstractions. Each Granule executes application code compiled to WebAssembly [16], a binary platform-independent execution format. The use of WebAssembly enforces lightweight memory safety: its isolation mechanism allows Granules to execute side-by-side in a single instance of the FAABRIC runtime. It also allows for an efficient snapshotting mechanism because the complete execution state of a Granule is captured in the single linear memory array of a WebAssembly module.

FAABRIC creates a Granule by restoring it from a *snapshot*,

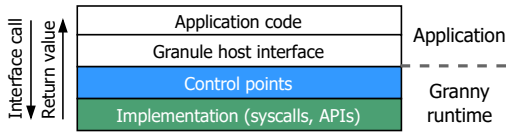


Figure 3: Control points (Control points are triggered when application code calls functions from supported APIs, before the FAABRIC implementation of the given function is executed.)

which has a copy of a Granule's execution state: its linear memory, mutable global variables, a function table and stack pointers. To restore a Granule, FAABRIC copies the stack pointer, function table and globals from the snapshot into the Granule, and creates a copy-on-write mapping of the Granule memory onto the snapshot's linear memory.

Fig. 2 shows how FAABRIC uses Granules and snapshots to replicate process and thread semantics across VMs. Each application has a *base snapshot*, whose linear memory contains the static data of the application. Granules restored from point-in-time snapshots of their parent Granules; Granules with *thread* semantics share a single linear memory mapping with other Granules on that VM.

3.2 Intercepting execution with control points

To execute and distribute scientific applications in a cloud environment, FAABRIC must interrupt the application execution periodically: it must (i) provision new Granules when the degree of parallelism used by the application changes; (ii) migrate Granules as dictated by the scheduler to improve locality and utilisation; (iii) synchronise shared memory between VMs; and (iv) deliver messages between Granules.

As shown in Fig. 3, FAABRIC triggers *control points* when an application invokes certain system calls and parallel programming APIs. Granules execute application code compiled to WebAssembly, and WebAssembly can pass control to the execution runtime for arbitrary listed functions. FAABRIC uses this approach to transfer control to the runtime on system calls related to thread and process operations, e.g. `pthread_create()` and `fork()`, as well as functions from OpenMP and MPI APIs, e.g. `MPI_Allreduce()`.

When making such function calls, control passes to the FAABRIC runtime at a control point. Before the runtime executes an API or system call implementation, it may perform one or more of the following actions: (a) spawn Granules to execute new logical threads/processes, e.g. on `fork()`; (b) await the completion of Granules to replicate joining a thread or awaiting process completion, e.g. on a call to `pthread_join()`; (c) merge changes to a shared address space using byte-wise diffs (§4), e.g. when completing OpenMP `parallel` sections; (d) send/receive messages between the Granules (§5.1), e.g. due to `MPI_Send()`; and (e) migrate a Granule (§3.3) to another host, e.g. on a call to `MPI_Barrier()`.

3.3 Migrating Granules across VMs

Cloud providers must retain control over the scheduling of Granules on VMs, e.g. to increase host utilisation or to co-

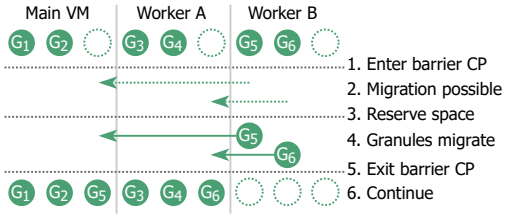


Figure 4: Granule migration at barrier control points

locate Granules belonging to the same tenant. FAABRIC achieves this control despite the long-lived execution of Granules because Granules can be *migrated* between VMs. Migration decisions are determined by a *scheduling policy*, e.g. bin-packing to the fewest VMs, load-balancing across VMs, or exploiting locality for Granules of a single application.

To simplify the migration process, Granule migration may only be carried out at *barrier control points*. These are control points that block all Granules of an application, e.g. as triggered by calls to OpenMP's `barrier` directive, MPI's `MPI_Barrier()` or `MPI_Allreduce()` functions.

Fig. 4 illustrates Granule migration. When Granules reach a barrier control point, they wait for a notification from the application's main VM. When the main Granule reaches the barrier control point on the main VM, it queries the *scheduler* for migration decisions. The scheduler, periodically and in the background, applies its scheduling policy and decides on function migrations if the current function execution deviates from the desired allocation. It then sends messages to all FAABRIC runtimes on the VMs involved in the migrations.

To migrate a Granule, the involved FAABRIC runtimes reserve the necessary resources for the Granules. If the resources have become unavailable, the migration is aborted. After that, the Granules to be migrated perform the migration and notify the main VM. Once the main VM has received notifications from all migrated Granules, it allows the Granules to exit the barrier control point.

The actual migration of a Granule is performed via the same mechanism that FAABRIC uses to create child processes and threads. The migrating Granule takes a snapshot, and sends the snapshot as part of a migration request to the target VM. The target VM creates a new Granule with the required semantics, i.e. with a new private mapping of the snapshot's linear memory for a process, or sharing a linear memory mapping with existing Granules for a thread.

3.4 FAABRIC architecture

Fig. 5 shows FAABRIC's architecture. A FAABRIC runtime executes on each VM, controlling a variable-sized pool of Granules, snapshots and message queues. Each Granule runs a single thread/process from an application.

FAABRIC uses a distributed shared state *scheduler*: the FAABRIC runtime on each VM has a *local* scheduler, which communicates with the other schedulers in the cluster. The local scheduler allocates up to one Granule per CPU core. If the thread or process executing in a given Granule requests

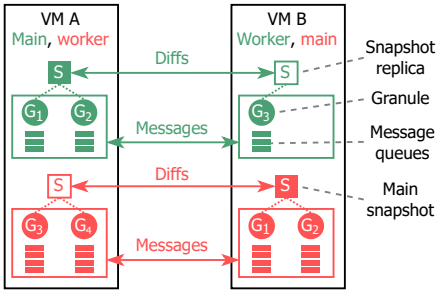


Figure 5: FAABRIC architecture (FAABRIC runtime instances act as either the *main* VM or *worker* VM for each application. They add, remove and migrate Granules, synchronise replicas of snapshots via byte-wise diffs, and asynchronously pass messages between Granules.)

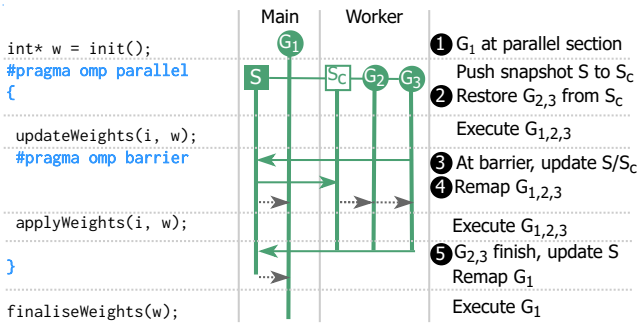


Figure 6: Synchronisation of a shared address space (Distributed Granules execute an OpenMP `parallel` section with a `barrier`.)

more parallelism, the local scheduler creates new Granules on that VM. If that VM has exhausted its CPU cores, the local scheduler chooses another VM, preferably one that already executes Granules for that application, as it then holds the application code and Granule snapshots in memory. If no such VM is available, the scheduler selects the VM with the most available resources. It then transfers the required snapshot to the new VM, and requests that it create and execute the new Granule.

Similar to most MPI implementations, FAABRIC currently does not offer fault-tolerance features—when one or more Granules fail, the whole application fails. Fault tolerance could be added to FAABRIC by exploiting Granule snapshots as checkpoints. If a Granule fails, the most recent snapshot can be restored, either on the same or on a different VM. Incoming messages to a Granule can be persisted by the local FAABRIC runtime until the next snapshot is reached, and replayed after Granule failure.

4 Shared Memory Programming

To execute multi-threaded applications correctly with shared memory, FAABRIC must provide consistency guarantees across Granules and VMs, alongside suitable synchronisation primitives. FAABRIC makes shared memory consistent by sending *byte-wise diffs* between Granules and VMs that communicate updates to the shared address space (§4.1).

Programming models such as OpenMP use *reductions* to aggregate parallel updates to shared variables without the coordination overhead of mutexes. FAABRIC supports reductions using *merge operations*, which allow it to combine multiple byte-wise diffs to the same memory region using arithmetic operations (§4.2). Finally, FAABRIC provides custom implementations of coordination primitives including mutexes, barriers and latches (§4.3).

4.1 Synchronising changes to shared memory

By default, multi-threaded applications assume only weak consistency guarantees on the memory shared between threads; stronger consistency is requested explicitly through synchronisation primitives. Assuming code is free from data races, FAABRIC must correctly execute multi-threaded applications: it must ensures that writes to shared memory from a child thread are visible to the parent thread when it joins that child. Changes must be visible to all threads when entering a critical section, or exiting an explicit or implicit barrier [45].

When FAABRIC needs to execute a child thread, it creates a new Granule from a snapshot of the main Granule. This snapshot is maintained until all child threads have finished execution, and acts as the *main snapshot* for the shared address space. FAABRIC synchronises all subsequent changes across Granules via this main snapshot: it receives updates to it from other Granules and VMs, and uses it to calculate updates to send to remote VMs.

A Granule maps its linear memory from the main snapshot if executing on the main VM, or a replica of the main snapshot if executing on a worker VM. The Granule then tracks the changes made to the shared address space by application code. FAABRIC write-protects all memory pages of the Granule's linear memory using `mprotect()` [25] and handles the page faults caused by application code by marking the page dirty and resetting its read/write permissions.

To send these changes back to the main VM when the Granule completes or reaches a barrier, the Granule performs a byte-wise comparison of the modified pages with its local copy of the main snapshot. This results in a list of *byte-wise diffs* that specify the offset at which the changes occurred and the modified bytes. The main VM receives these byte-wise diffs from worker VMs and uses them to update the main snapshot.

The FAABRIC runtime must update the main snapshot replicas on remote VMs, e.g. when exiting a barrier. It transmits only the byte-wise diffs required to update the remote replicas, and not the whole snapshot. To enable this, the FAABRIC runtime on the main VM keeps track of which bytes have been updated by incoming byte-wise diffs, then sends a new set of byte-wise diffs with these changes to the worker VMs.

Fig. 6 gives an example of shared memory synchronisation, which shows how FAABRIC executes an implementation of the SGD example (Listing 1) using 3 Granules across 2 VMs. ❶ When the main Granule enters an OpenMP `parallel` sec-

```
int n = get_max_num_threads()
int[] w = initWeights(n);

#pragma omp parallel {
  int t = omp_get_thread_num();
  w[t] = updateWeight(w, t, n);
}

applyWeights(w);
int x = 0;

#pragma omp for reduction(+:x) {
for(int i=0; i<n; i++) {
  x += w[i] > threshold ? 1 : 0;
}
```

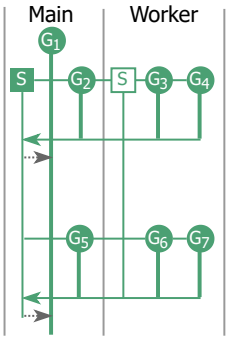


Figure 7: Reductions in OpenMP (Granules on 2 VMs make non-conflicting updates in a `parallel` section, and perform a reduction.)

tion, it triggers a control point at which FAABRIC creates the main snapshot of the shared address space from the main Granule. ❷ FAABRIC then creates 2 more Granules from a replica of this main snapshot on the worker VM, and each Granule executes the body of the `parallel` section. ❸ When all Granules have reached the `barrier`, each creates a list of byte-wise diffs that the FAABRIC runtime on the main VM uses to update the main snapshot. ❹ On exiting the barrier, the main VM's FAABRIC runtime sends another list of byte-wise diffs to update the snapshot replica on the worker VM. All Granules then remap their own linear memory to the local copy of the snapshot and continue execution. ❺ At the end of the `parallel` section, the parent Granule joins the child Granules, and again FAABRIC uses the byte-wise diffs from each Granule to update the main snapshot. Finally, the main Granule remaps its memory from the snapshot.

4.2 Supporting reductions on shared variables

Declarative multi-threading frameworks such as OpenMP allow multiple threads to aggregate changes to shared variables using *reductions* [46]. A reduction spawns multiple threads that update one or more shared variables in parallel, then aggregates those updates once all threads have completed execution, e.g. via a summation. By deferring the aggregation of concurrent updates to shared variables until threads have completed, we can avoid the overhead that would otherwise be incurred from synchronising those updates using a mutex. FAABRIC distributes multi-threaded applications, hence reducing synchronisation between threads via reductions reduces cross-VM coordination overheads.

To distribute reductions in FAABRIC, the runtime on each VM performs the reduction operation locally for the Granules executing on that VM, then transmits its updates back to the main VM as a byte-wise diff. For each byte-wise diff sent back to the main VM, FAABRIC specifies a *merge operation*, with the arithmetic operation that should be used to apply that byte-wise diff to the main copy of the shared variable.

Fig. 7 shows OpenMP code for a `parallel` section that performs disjoint updates to a shared vector and a `reduction` section to update a shared variable via a summation. FAABRIC spawns 3 child Granules when the main Granule reaches the parallel section, creating the main snapshot on the main VM and a replica on the worker VM. Each Granule maps its linear memory from its local copy of the snapshot.

Merge operation	Formula	Data types
sum	$A_1 = A_0 + (B_1 - B_0)$	All numeric
subtract	$A_1 = A_0 - (B_0 - B_1)$	All numeric
multiply	$A_1 = A_0 * (B_1 / B_0)$	All numeric
divide	$A_1 = A_0 / (B_0 / B_1)$	All numeric
overwrite	$A_1 = B_1$	Arbitrary bytes

Table 3: Merge operations supported by FAABRIC. (FAABRIC overwrites the original value A_0 in the main snapshot with value A_1. B_0 is the value seen in the snapshot on the remote VM before the Granule executed, and B_1 is the value after execution.)

In the first parallel section, each Granule updates its value in the `w` vector. The resulting byte-wise diffs can be written directly to the main snapshot without a merge operation. In the `reduction` section, each thread updates their local copy of the variable `x`, generating a byte-wise diff on the same memory region. Since the `reduction` specifies a summation over `x`, FAABRIC combines these byte-wise diffs in the main snapshot using a `sum`.

Tab. 3 lists the merge operations supported by FAABRIC. They include simple arithmetic operations of summation, subtraction, multiplication and division, as commonly found in parallel reductions. The operations involve four values: A_0, the starting value in the main snapshot; B_0, the value held in the copy of the snapshot on the remote VM; B_1, the updated value after the thread has executed on the remote VM; and A_1, the value written to the main snapshot by the operation.

4.3 Synchronisation primitives

In addition to providing shared memory and reduction operations, FAABRIC must support the synchronisation primitives in multi-threaded code that control concurrent access to shared data. FAABRIC offers the following primitives:

Mutexes. A mutex guarantees that only one Granule can access data at a given time. In FAABRIC, application code that acquires a mutex triggers a control point, and the associated Granule requests a lock on the mutex from the FAABRIC runtime. When locking the mutex, the FAABRIC runtime returns the byte-wise diffs to update that Granule's local copy of the shared memory snapshot. This way, the Granule holding the mutex is guaranteed to observe the updates of other Granules that have also held it; when releasing the mutex, the Granule returns its own set of byte-wise diffs to the FAABRIC runtime.

Atomic operations. Atomic arithmetic operations do not guarantee consistency, only atomicity. To perform such operations, each Granule acquires a VM-local mutex to avoid data races on the local copy of the shared memory. FAABRIC then uses a merge operation corresponding to the arithmetic operation to merge the resulting byte-wise diffs.

Barriers. A barrier is either implicit or explicit: an implicit barrier is introduced by a `parallel` section; an explicit barrier is added manually. Barriers require that all Granules block

until they have completed the barrier. Afterwards, all Granules must observe a consistent view of the shared memory. On entering a barrier, Granules send their byte-wise diffs to the main VM and block. After all threads have completed, the main VM sends the aggregated byte-wise diffs to all Granules, which unblock.

Latches. A latch allows Granules to decrement a counter and/or wait for it to reach zero. Latches are used implicitly in `nowait` OpenMP operations: the main Granule blocks until all child Granules have reached the latch. Granules can make non-blocking requests to the main VM to decrement a latch, or blocking requests to wait for the latch to reach zero.

5 Message Passing

To support multi-process applications with message passing, FAABRIC must associate Granules with long-lived identities for communication. FAABRIC organises Granules into *Granule groups*, in which each Granule is assigned an index. It can then asynchronously send and receive messages to and from other Granules in the group by referring to that index (§5.1).

When migrating Granules between VMs, each FAABRIC runtime instance updates its local Granule group metadata to ensure consistent message delivery independent of each Granule's placement (§5.2). For efficient collective communication, FAABRIC provides Granule group-aware implementations of operations such as all-reduce and broadcast, maximising fast intra-VM messaging via in-memory data structures (§5.3).

5.1 Communication in Granule groups

Each Granule that executes a process in a multi-process application may need to send messages directly to another Granule, e.g. to fulfil API calls in a message-passing framework such as MPI. To enable such message passing efficiently, FAABRIC allows asynchronous messaging between Granules within a Granule group. The asynchronous nature of FAABRIC's message passing avoids blocking a sender Granule while the receiver Granule is being migrated or initialised.

By default, all Granules that execute an application are in the same Granule group. FAABRIC may create new Granule groups on control points, e.g. as triggered by `MPI_Comm_create()`, which allows the application to control communication groups. A Granule group assigns each Granule an *index*, which FAABRIC uses as an address for that Granule in its implementation of message passing APIs. Each FAABRIC runtime that executes a Granule holds a replica of the Granule group metadata with an *address table* that maps the indexes of Granules in the Granule group to the VM on which they have been scheduled. For each Granule of the group executed on a VM, the FAABRIC runtime has a set of queues to buffer messages sent to that index.

When a Granule triggers a control point that requires sending a message, e.g. `MPI_Send()`, the FAABRIC runtime on the VM of the sending Granule looks up the recipient index in the address table for that group. If the recipient is on the same VM, FAABRIC directly enqueues the message on the relevant in-memory queue. This results in low-latency intra-VM messaging compared to using the local loopback network interface or inter-process communication (IPC). If the recipient is on another VM, FAABRIC sends the message to the runtime on that VM, where it is enqueued.

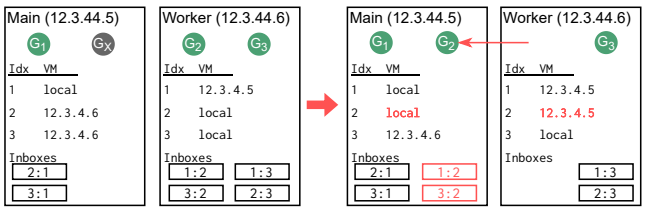


Figure 8: Preserving a Granule group while migrating (One Granule from the Granule group is migrated from a worker VM to the main VM, and FAABRIC updates the metadata and queues.)

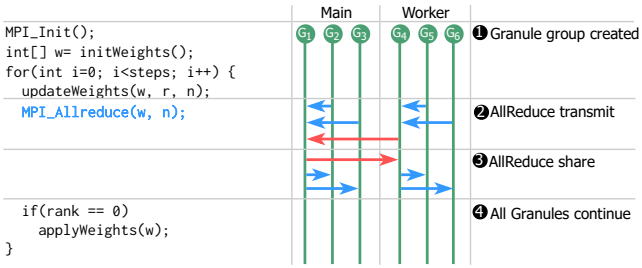


Figure 9: MPI collective communication (A VM-leader on each VM sends/receives intra-VM messages (blue) and sends/receives cross-VM message (red) to/from other VM-leaders.)

5.2 Groups when migrating Granules

When migrating Granules across VMs (§3.3), the FAABRIC runtimes must also update the metadata and queues associated with Granule groups to which the migrating Granules belong.

Fig. 8 shows how FAABRIC updates a Granule group during migration. Initially, the main VM executes one Granule from the group alongside a Granule from another application; the worker VM executes two other Granules from the group. When the Granule from the other application completes, it frees up resources on the main VM; when the Granules reaches a barrier control point, FAABRIC migrates one of the Granules from the worker VM to the main VM. Before completing the migration, each FAABRIC runtime updates its address table and creates or deletes queues to accommodate the new or departing Granule, respectively.

To avoid issues with message delivery arising from migrated Granules while messages are in-flight or queued, FAABRIC only inserts barrier control points on message passing operations where Granules in worker VMs are waiting for one Granule in the main VM, e.g. MPI's `MPI_Barrier()`, `MPI_Allreduce()` and `MPI_Gather()`. This way, FAABRIC guarantees that there are no messages in-transit.

5.3 Collective communication

In addition to simple point-to-point messaging, most message passing applications make use of *collective communication* operations, such as all-reduce and broadcast. These operations are widely used in distributed ML training through specialised libraries [12, 49, 66]. FAABRIC uses custom Granule group-aware implementations of these operations, which minimise latency by exploiting knowledge of Granule placement to maximise intra-VM messaging.

Fig. 9 shows the message passing performed by FAABRIC when application code makes a call to `MPI_Allreduce()`. ❶ When FAABRIC creates a Granule group, it selects one Granule on each VM to be the *VM-leader* for that VM. Any messages that need to be sent to Granules on other VMs are sent by all Granules to their VM-leader, which batches the messages into single cross-VM requests. All-reduce takes place in two steps: ❷ an initial reduce in which results from all Granules on each VM are sent to the main VM via their VM-leader; and ❸ a broadcast of the final result to all Granules, which is delivered via their VM-leader.

FAABRIC's implementation of collective communication operations reduces the cross-VM messages to one per remote VM involved in each step. It then uses fast in-memory queues for the Granule to VM-leader communication. This approach reduces latency (§6.5) and bandwidth usage, and enables pipelining: after a Granule has asynchronously messaged its local leader, it can continue execution.

6 Evaluation

Our evaluation answers the following questions: (i) what are the benefits of using FAABRIC to run scientific applications on shared VMs? (§6.2); (ii) what is the impact of the cluster size on FAABRIC? (§6.3); (iii) what is the performance overhead of executing shared memory applications using Granules? (§6.4); (iv) what is the performance overhead of executing message passing applications using Granules? (§6.5); and (v) what is the performance overhead when migrating Granules at runtime? (§6.6)

6.1 Experimental set-up

Implementation. FAABRIC is written in 24,000 lines of C++20, compiled using clang-13, and available as open-source at: *removed for anonymity*. Deployed applications and all transitive dependencies, e.g. *libc*, are compiled to WebAssembly [16] using clang-13 [51], as part of the FAABRIC CPP toolchain, also available as open-source at: *removed for anonymity*. The batch scheduler is written in 1000 lines of Python, and is available at: *removed for anonymity*.

Test-bed. We deploy FAABRIC and OpenMPI on a Kubernetes cluster [21] on Azure [31]. The cluster has 32 *Standard_D8_v5* VMs [33] with 8 vCPU cores and 32 GB of memory. Native OpenMP applications execute using the underlying VMs in. We implement a batch scheduler that monitors cluster resources and executes jobs as soon as there are enough free resources (in terms of vCPUs).

Workloads. We evaluate FAABRIC with scientific applications written using OpenMP [45] for shared memory, and MPI [40] for message passing. We compare these applications running on FAABRIC against native implementations running directly on VMs. All OpenMP code is compiled using clang-13 (OpenMP v4.5) [27], and we use OpenMPI v4.1 [47]. FAABRIC is deployed using Kubernetes (K8s) [21].

6.2 Efficiency of running scientific applications

We explore the efficiency and performance impact of using FAABRIC to execute applications on a shared VM cluster. As a workload, we generate a trace of 100 jobs. Each job executes a scientific application with a different level of parallelism specified by MPI's world size (as indicated in the `mpirun` command) or by the `OMP_NUM_THREADS` environment variable.

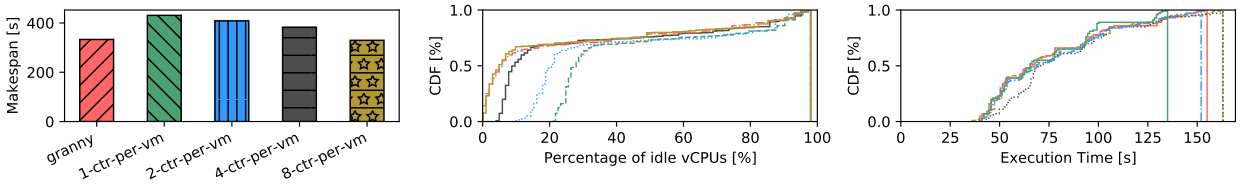
We generate two traces: one with message passing applications (`mpi`), and one with shared memory applications (`omp`). For the message passing applications, we use LAMMPS [50, 55], a popular molecular dynamics simulator written in C++ using MPI. We pick the Lennard-Jones (LJ) atomic fluid simulation with 4 million atoms, as it is one of the standard benchmarking problems in the LAMMPS suite [56]. For the shared memory application, we run a dense matrix multiplication (DGEMM), part of the ParRes kernels [48].

As baselines, we want to compare to different VM sizes, exhaustively exploring the fragmentation space: larger VM sizes (i.e. higher vCPU counts and larger memory amounts) yield higher per-job performance but result in more idle vCPUs; smaller VM sizes lead to lower per-job performance but fewer idle vCPUs. To avoid managing different VM pools with different VM sizes, we deploy a single VM pool (32 *Standard_D8_v5* VMs) and emulate smaller VMs by using 1, 2, 4, or 8 containers, enforcing an even vCPU/memory split using K8s resource limits [22]. Different jobs execute in different containers: MPI jobs take up $\lceil \frac{\text{MPI world size}}{\text{vCPUs per ctr}} \rceil$ containers; OpenMP jobs use 1 container, overcommitting vCPUs to threads if `OMP_NUM_THREADS` > vCPUs per container.

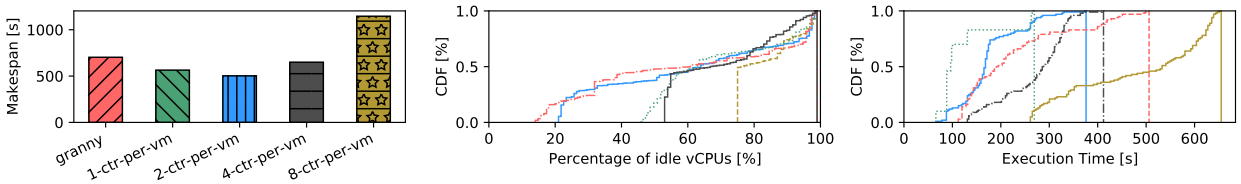
We configure the batch scheduler to schedule jobs in sequence, as soon as there are sufficient vCPUs. This means that the scheduling granularity becomes important: if the cluster is fragmented, jobs will wait for longer in the queue, increasing makespan; over-fragmenting jobs to pack them tightly will increase their execution time, also increasing makespan.

Fig. 10 shows the results. For each job trace (`mpi` in Fig. 10a and `omp` in Fig. 10b), we report the total time to execute the 100 jobs (i.e. makespan), the CDF of the percentage of idle vCPUs in the cluster, and the CDF of job execution times.

In terms of makespan, MPI jobs in FAABRIC have a 13%–23% lower makespan compared to all fixed-sized baselines except for `8-ctr-per-vm`. `8-ctr-per-vm` is equivalent to running each MPI process in a separate container. Given the MPI's message passing nature, this approach is acceptable and per-



(a) Execution of 100 MPI jobs (Requested parallelism distributed uniformly from 4–16 vCPUs/MPI processes)



(b) Execution of 100 OpenMP jobs (Requested parallelism distributed uniformly from 2–8 vCPUs/OpenMP threads)

Figure 10: Execution breakdown of running a trace with 100 jobs (We report the total time elapsed, i.e. makespan; the CDF of idle vCPUs; and the CDF of job execution times.)

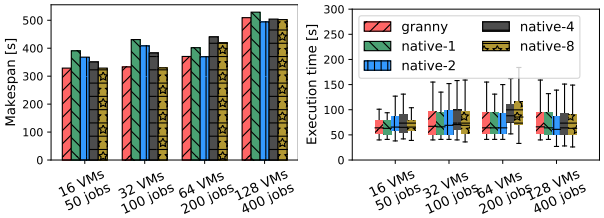
forms on-par with FAABRIC. For OpenMP jobs, however, using 1 container per vCPU reduces performance: FAABRIC's makespan is 38% lower than `8-ctr-per-vm`'s. However, FAABRIC has between 8% and 25% higher makespan than the other baselines. This is due to the overhead of FAABRIC's shared memory implementation (see §6.4). In summary, FAABRIC achieves lower makespan than the native baselines, reducing both user costs and provider under-utilisation.

To understand why FAABRIC reduces the makespan, we analyse the CDF of the percentage of idle vCPUs, and the CDF of the job execution time. For MPI jobs, half of time, FAABRIC has at most 5% of idle vCPUs, whereas the native baselines leave 10%–30% of vCPUs idle (with the exception of `8-ctr-per-vm`). This shows that FAABRIC better utilised the available vCPUs by packing and distributing jobs at a finer granularity using Granules. For OpenMP, 100 jobs are not enough to saturate the cluster, specially for baselines that over-commit. Per-job execution time in FAABRIC is on-par with all baselines for the MPI jobs, with the exception of the last 15% of jobs – these jobs take longer to execute because they are over-fragmented. For OpenMP jobs, FAABRIC's execution time becomes worse than the baselines due to the overhead of shared memory executions. In summary, FAABRIC achieves lower makespan by allocating resources at finer-grained granularity, paying the price of over-fragmenting some jobs, making them run for longer.

6.3 Scalability

We explore FAABRIC's scalability with respect to the number of VMs in the cluster. As a workload, we use traces of 50, 100, 200 and 400 MPI jobs in a cluster with 16, 32, 64 and 128 *Standard_D8_v5* VMs, respectively. We measure the makespan and the average job execution time. By increasing the number of tasks with the cluster size, we expect the makespan to stay constant. We use the same batch scheduler configuration and baselines from §6.2.

In Fig. 11, we report, for each cluster size, the makespan (Fig. 11a) and the distribution of execution times with a box plot that includes the median, boxes for the 25th and 75th percentiles, and whiskers extending 1.5× the inter-quartile range (Fig. 11b).



(a) Makespan **(b) Job execution time**

Figure 11: Scaling the VM count (We report the makespan to execute a batch of jobs, which increases linearly with cluster size, and the distribution of execution times.)

FAABRIC achieves a 7%–16%, 13%–23% and 10%–20% lower makespan for 16, 32 and 64 VMs respectively, because it manages to utilise the cluster resources more efficiently. Its makespan is on par with `native-8`, as explained in §6.2. Note that the makespan values for 16–64 VMs vary within 5%–10% of each other, which is caused by the different job sizes in each trace. For 128 VMs, however, the performance of all deployments degrades due to the implementation of our centralised batch scheduler, which becomes a bottleneck. FAABRIC's makespan also is 5% higher than the baselines because FAABRIC's current implementation centrally manages all registered VMs and their resources.

To explore this performance degradation further, Fig. 11b shows the distribution of execution times for each baseline and cluster size using a boxplot. Each job in the trace has a different level of parallelism, and longer traces have more jobs, introducing randomness. In spite of this randomness, Fig. 11b shows that the 25th, median, and 75th percentiles are very similar across baselines, and cluster sizes. The whiskers are more variable, as they account for the tails of the distribution. These results confirm our hypothesis that the performance degradation in Fig. 11a is due to limitations of FAABRIC's cluster

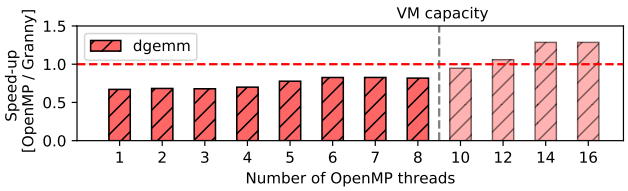


Figure 12: Speed-up executing shared memory applications (When the number of threads spans multiple VMs, we compare FAABRIC's time with OpenMP's execution time with 8 threads.)

management and batch scheduler implementation, rather than Granules. These limitations can be overcome with additional engineering work or by deploying FAABRIC across multiple 64 VM clusters, and load-balancing requests across them.

6.4 Shared memory performance

Next we investigate the performance overhead introduced by FAABRIC when executing shared memory applications using OpenMP. We use the same OpenMP application from §6.2: a dense parallel matrix multiplication (DGEMM) from ParResKernels [48]. DGEMM is computationally-intensive, with some light use of FAABRIC's shared memory synchronisation and coordination primitives.

Fig. 12 shows the speed-up achieved by FAABRIC, computed as the ratio between native OpenMP and FAABRIC's execution time. We execute both baselines with different numbers of OpenMP threads: native OpenMP cannot be scaled out, limiting its parallelism to that that of 1 VM (i.e. 8 vCPU cores, with each thread pinned to one core); FAABRIC can scale out shared memory applications using Granules. For distributed execution (i.e. with thread counts greater than 8; faded bars in Fig. 12), we measure the speed-up as the native execution time with 8 OpenMP threads divided by FAABRIC's execution with the higher thread count.

For DGEMM, FAABRIC is 20%–30% slower than native OpenMP in a single VM, due to the overhead of performing floating-point arithmetic in WebAssembly [18]. When scaling out to another VM, FAABRIC achieves the optimal native performance in one VM with 50% more threads. FAABRIC achieves a 25% speed-up (over native OpenMP with 8 threads) when executing with twice as many threads. In summary, FAABRIC distributes shared memory applications with Granules, surpassing the performance of a single VM deployment.

6.5 Message passing performance

This experiment explores FAABRIC's performance overhead when executing message passing applications using MPI. We run the same MPI application as in §6.2: the LAMMPS simulator running the Lennard-Jones (LJ) benchmark with 4 million atoms. To stress FAABRIC's communication layer, we update LAMMPS' *controller* example [57] and increase the synchronisation steps, resulting in three orders of magnitude more cross-VM messaging. We refer to the LJ benchmark as *compute-bound*, and the modified *controller* one as *network-bound*. We also run a subset of the ParRes kernels [48] to

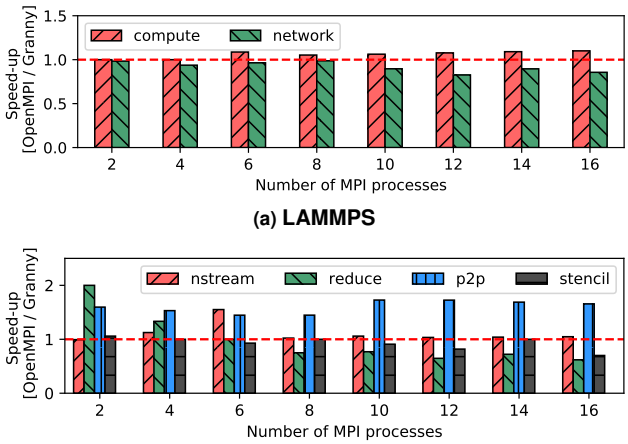


Figure 13: Speed-up executing message passing applications

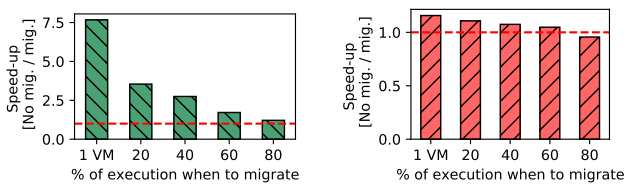
evaluate specific parts of FAABRIC's implementation.

Fig. 13 shows the speed-up that FAABRIC achieves, computed as the ratio between OpenMPI's and FAABRIC's execution times. We execute the two LAMMPS simulations (Fig. 13a) and the ParRes kernels (Fig. 13b) with different levels of parallelism.

For LAMMPS' compute-bound benchmark, FAABRIC achieves a 5%–10% speed-up over OpenMPI. FAABRIC slightly outperforms OpenMPI due to the faster intra-VM messaging using shared memory and the locality-aware collective communication implementation. For the network-bound benchmark, FAABRIC's execution time is up to 15% higher than OpenMPI's. This slow-down is due to an additional level of indirection in FAABRIC's transport layer to support concurrent applications, which becomes a bottleneck with higher message throughputs.

To analyse the performance of different parts of FAABRIC's message passing implementation further, we execute ParRes kernels [48] for distributed computation. For the point-to-point messaging kernel (`p2p`), FAABRIC achieves a 50%–70% speed-up over OpenMPI because most messages are intra-VM, and FAABRIC can use in-memory queues. The `nstream` kernel updates an array in streaming fashion and synchronises with a barrier, and FAABRIC matches the OpenMPI performance. For the reduction kernel (`reduce`), FAABRIC is between 25% faster and 25% slower in a single VM, and 25%–50% slower when distributing MPI processes over 2 VMs. FAABRIC performs worse than OpenMPI when there are more cross-VM messages, as previously discussed. Finally, for the `stencil` kernel, FAABRIC is up to 30% slower because cross-VM messages dominate execution.

In summary, FAABRIC's message passing performance is comparable to that of OpenMPI. FAABRIC performs best for intra-VM messages, as it can use its in-memory queues, and worst for cross-VM messages, which add extra overhead.



(a) All-to-all **(b) LAMMPS**

Figure 14: Speed-up when migrating Granules (We deploy 8 MPI processes fragmented across two VMs and migrate 4 at runtime. We report the speed-up compared to not migrating.)

6.6 Migration of Granules

This experiment measures the benefit of migrating Granules at runtime. As baselines, we run a compute-bound LAMMPS simulation, and a network-bound *all-to-all* kernel that performs synchronisation over a vector in a loop. To migrate a function, FAABRIC must guarantee that there are no messages in-flight, and it uses calls to barrier synchronisation points to check for migration opportunities.

Fig. 14 shows the speed-up achieved when migrating. We force the scheduler to over-fragment the jobs, and then migrate at 20%, 40%, 60%, or 80% of execution. For reference, we also include the speed-up for a co-located deployment (1 VM).

For a network-bound kernel, over-fragmenting has a high cost: the speed-up for 1 VM is 7.5×. By migrating after 20%, 40%, 60%, and 80%, of execution, we achieve speed-ups of 3.5×, 2.7×, 1.7×, and 1.2×, respectively. We conclude that it is always worth to migrate Granules at runtime for network-bound applications.

For a compute-bound kernel, over-fragmenting has a lower cost: the speed-up for 1 VM is 1.2×. This is because the fragmentation splits 4 processes in 1 VM, and 4 processes into another, which means that there is substantial intra-VM messaging. By migrating after 20%, 40%, and 60% of execution, we achieve speed-ups of 10%, 8%, and 5%, respectively. When migrating after 80% of execution, the costs of migrating outweigh its benefits, achieving a slow-down of 5%. LAMMPS has large code and data sections, which leads to larger Granule snapshot, increasing the cost of migration.

7 Related Work

Scientific applications in the cloud. Nowadays, all major cloud providers offer targeted solutions to support scientific applications in the cloud [7, 36, 37]. To schedule and execute these applications, providers deploy batch scheduling solutions [3, 30] inspired by HPC batch schedulers, and there is related work focuses on optimising scheduling decisions [24]. Instead, FAABRIC focuses on utilising scheduled resources more efficiently—an orthogonal problem to better scheduling decisions. Recent work on scheduling for deep learning training on shared GPU clusters [64] uses traits of the scheduled resources to improve scheduling decisions, and we plan on exploring this in the future.

Shared memory and message passing in the cloud. Hoplite [66] uses well-known collective communication algorithms for building fault-tolerant task-based distributed systems. FAABRIC adopts a similar approach: it focuses on dynamic group membership without considerations of fault-tolerance; Ray [39] is a distributed system that unifies task-parallel and actor-based computations in a single interface. It offers transparent state and message passing irrespective of the distribution, together with transparent unlimited scaling. FAABRIC focuses on sharing resources among multiple users more efficiently.

Fine-grained distribution in serverless. FAABRIC borrows techniques from research on serverless runtimes to allow fine-grained scheduling and distribution of scientific applications. Faasm [60] and Cloudburst [61] add state to serverless functions, but do not provide generic shared memory required for multi-threading, nor do they support message passing; PLASMA [58] supports annotations to specify elasticity constraints but only within an actor-based programming model; Crucial [8] uses Java concurrency abstractions to execute serverless functions, but it lacks general multi-threading capability. The lack of communication primitives in serverless has been recognised as a limitation: SAND [2] includes a message bus, but does not provide an associated programming model to support collective communication.

Checkpointing and Migration. CloudScale [59] automates fine-grained elastic resource scaling in a shared (multi-tenant) cluster. CloudScale also uses migration to correct scheduling or scaling issues. FAABRIC could benefit from being used together with CloudScale, as it allows for finer-grained resource management, allowing CloudScale to operate at a thread/process level rather than at a VM one. CRIU [11] is a software tool for checkpointing and restoring processes in userspace. FAABRIC's use of WebAssembly means that snapshot can be obtained more easily without using CRIU or other similar tools such as DMTCP [14].

8 Conclusions

Cloud computing offers on-demand parallelism that is well-suited to scientific workloads. Today's cloud services for scientific applications execute workloads on dedicated VMs, which reduces providers' abilities to re-allocate underused resources. Serverless cloud computing promises to overcome these issues through the fine-grained allocation of tasks to resources.

We have described FAABRIC, a new cloud runtime that transparently distributes scientific workloads at a fine granularity while remaining compatible with the popular OpenMP and MPI APIs. FAABRIC relies on Granules, which permit the arbitrary distribution of threads and processes. Its scheduler allocates Granules in a flexible fashion, allowing Granules to exchange messages asynchronously and supporting a distributed shared memory implementation.

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