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Empirical Study of Actor-based Runtime Verification

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Abstract

In this work, we study how the use of concurrent monitors in a runtime verification system can improve performance when combined with different layers of indexing. We specifically target concurrent monitoring systems that adopt the actor programming model which is one way of developing concurrent systems. We employ monitoring systems which are built using our runtime verification framework, MESA (MEssage-based System Analysis). MESA allows for building actor-based monitoring systems that check for properties specified in data parameterized temporal logic and state machines. We performed the empirical study by conducting experiments with monitoring systems that include different numbers of monitor actors and different layers of indexing. This report describes our experiments, and evaluates our results. The evaluation shows the value of concurrency in the context of runtime monitoring.

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1 Introduction

This report presents our empirical study which was conducted to evaluate the impact of concurrent monitors in a *runtime verification* system. Runtime verification is a dynamic technique that checks if a run of the system under observation satisfies a property of interest [1,2]. Properties are usually specified as formal specifications expressed in forms of linear temporal logic formulas, finite state machines, regular expressions, etc.

We use the runtime time verification framework MESA in the experiments. MESA is written in Scala and adopts the actor programming model [3] implemented in the Akka toolkit [4, 5]. The runtime verification systems built using the MESA framework are actor-based, that is, they are solely composed of *actors* which are lightweight, dedicated components that do not share states and can only communicate via exchanging asynchronous messages. Each MESA system includes four steps, which are also adopted by most runtime verification tools, data acquisition, data processing, monitoring, and reporting. Figure 1 illustrates an example of a MESA system.

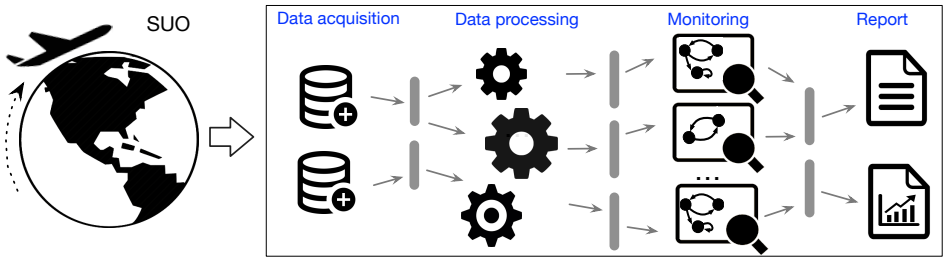


Figure 1: *An example of a monitoring system building using the MESA framework*

MESA uses the platform Runtime for Airspace Concept Evaluation (RACE) [6,7] as an external library. RACE allows for generating airspace simulations. RACE is also built on top of the Akka toolkit, and extends it with additional features that our framework relies on. MESA also incorporates the tools TraceContract [8, 9] and Daut [10, 11] to support property specification to check for properties specified in data parameterized temporal logic and state machines. These tool are implemented as internal DSLs written in Scala. In this study we use Daut to implement the property of interest.

The focus of the study is to explore the impact of concurrent monitors for runtime verification when combined with different layers of *indexing*. Indexing can be seen as a restricted from of slicing that using a slicing criteria, it slices the trace up into sub-traces which are then fed to sub-monitors.

2 Property of Interest

For the experiment, we used the SWIM Flight Data Publication Service (SFDPS) [12, 13] as the system under observation. SWIM is a highly distributed system that consolidates data from many sources. We have observed incidents where

the SFDPS messages are not distributed in the right order by the SWIM server. We choose `sfdps-seq-order` as the property of interest for this experiment which checks for the chronological order of the SFDPS messages, that is, it verifies that the SFDPS messages with the same *call sign* (flight identifier) are ordered by their time tags. This property is specified as a data-parameterized finite state machine using the Daut DSL [10, 14]. The class `sfdpsOrderMonitor` which is presented in Figure 2 implements `sfdps-seq-order`. The property `sfdps-seq-order` is implemented as a Daut monitor which is illustrated in Figure 2. The `daut.Monitor` is the key class in Daut that implements the monitor capabilities. A Daut monitor maintains the set of all active states representing the current states of the state machines. A state is presented by an object of type `state`, and the set of transitions out of the state is presented by a `Transitions` object. `Transitions` is defined as a partial function `PartialFunction[E,Set[state]]` where E is a monitor type parameter.

```
trait MesaMonitor {
  def verifyEvent(event: Any): Unit
}

class DautMonitor(val config: Config) extends daut.Monitor[Any] with MesaMonitor {
  def verifyEvent(event: Any) : Unit = {
    verify (event)
  }
}

class sfdpsOrderMonitor(config: Config) extends DautMonitor(config){
  always {
    case FlightState(_, cs, _, _, _, _, date1, _) =>
      watch {
      case FlightState(_, `cs`, _, _, _, _, date2, _)=> {
        date2.isAfter(date1)
      }
    }
  }
}

class sfdpsOrderMultiMonitor(config: Config) extends DautMonitor(config){
  val size = config.getInt("sub-monitor-count") - 1
  val m = for(i <- 0 to size) yield new sfdpsOrderMonitor(config)
  monitor(m: _*)
}
```

Figure 2: *Daut monitor capturing the property* `sfdps-seq-order`

The functions `always` and `watch` in Figure 2, which are defined in `daut.Monitor`, act as states. They accept as argument a partial function of type `Transitions` and return an object of type `state`. The `case` statements defined within `always` and `watch` represent transitions at states which are matched against incoming events. `FlightState` and `TrackCompleted` are the two possible events in

the input trace. The events are defined as Scala case classes since the built-in pattern matching support in Scala facilitates the implementation of data-parametrized state machines. The parameter `cs` represents the flight call sign. For each incoming event fed to the monitor object, the method `verify` is invoked which creates new target states, if any, from the transitions, and updates the set of the active states.

Daut provides an indexing capability within monitors to improve their performance. It allows for defining a function from events to keys where keys are used as entries in a hash map (of type `scala.collection.immutable.HashMap`) to obtain those states which are relevant to the event. Using this approach, a Daut monitor only iterates over an indexed subset of states instead of the entire set of current states. To use Daut indexing in a monitor, one needs to override the method `keyOf` of `daut.Monitor`. Some of the actor-based systems used in the experiment employ Daut indexing which is implemented by the class `sfdpsOrderMonitor_indx`. As shown in Figure 3, `sfdpsOrderMonitor_indx` overrides `keyOf` with an implementation that given an event, returns the call sign associated with the event.

The `sfdps-seq-order` property is simple and it leads to a small *service time*, which is the time used to process the message within the monitor objects. To mitigate issues associated with microbenchmarking on JVM, we use a feature of Daut that allows for defining sub-monitors within a Daut monitor object. A microbenchmarking deals with evaluating small tasks, and due to optimizations and mechanisms such as garbage collection, it is often difficult to obtain precise evaluation on JVM. By defining sub-monitors, we can increase the monitors *service time*. We define the class `sfdpsOrderMultiMonitor` (Figure 2) which is a Daut monitor and maintains a list of `sfdpsOrderMonitor` instances as its sub-monitors. The size of the list is provided by the user in the configuration file using the key `sub-monitor-count`. Similarly, the class `sfdpsOrderMultiMonitor_indx` (Figure 3) is defined which maintains a list of `sfdpsOrderMonitor_indx` instances as its sub-monitors.

```
class sfdpsOrderMonitor_indx(config: Config) extends sfdpsOrderMonitor(config){
  override protected def keyOf(event : Any): Option[String] = {
    event match {
      case FlightState(_, cs, _, _, _, _, _, _) => Some(cs)
      case TrackCompleted(_, cs, _, _, _, _, _, _) => Some(cs)
    }
  }
}

class sfdpsOrderMultiMonitor_indx(config: Config) extends DautMonitor(config){
  val size = config.getInt("sub-monitor-count") - 1
  val m = for(i <- 0 to size) yield new sfdpsOrderMonitor_indx(config)
  monitor(m: _*)
}
```

Figure 3: *Daut monitor capturing the property* `sfdps-seq-order` with indexing

3 Monitoring Systems

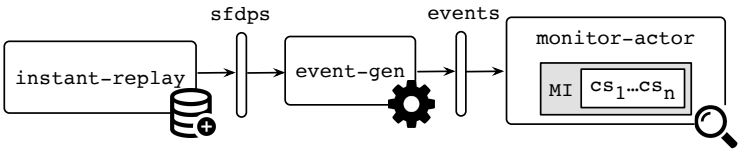
This section presents the actor-based monitoring systems used in our experiment. These systems are illustrated in Figure 4. The outermost white boxes represent actors and the vertical lines between them represent the publish/subscribe communication channels. It can be seen that all the systems have the same data acquisition and data processing phases, and they are only different in their monitoring phase. They use the `instant-reply` actor to acquire the input data and the `event-gen` actor to process the data. The `instant-reply` actor accesses an archive containing recorded SFDPS data messages in the XML format, and as it reads the messages, it publishes them to the `sfdps` channel instantly. The `event-gen` actor obtains the XML messages by subscribing to the channel `sfdps`, turns each message into an event of type `FlightState` or `TrackCompleted`, and publishes the event object to the channel `events`. `FlightState` captures the state of the flight, and `TrackCompleted` indicates that the flight has reached its final destination.

MESA provides components referred to as dispatchers which are configurable and used in the monitoring phase of the runtime verification to determine how the check for the property of interest is distributed among different *monitor actors*. The actors that contain one or more monitor instances are referred to as monitor actors. The MESA dispatchers which are implemented as actors are not tied to a specific application and they can be extended towards different systems under observation. As explained below, these components are key to our experiments.

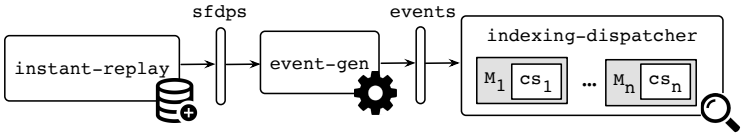
Let `n`, in Figure 4, be the total number of different call signs in the input sequence of SFDPS messages. The gray boxes inside the actors represent monitor instances, where `M` refers to instances of type `sfdpsOrderMultiMonitor` (Figure 2) and `MI` refers to instances of type `sfdpsOrderMultiMonitor_indx` (Figure 3). The white box contained inside each monitor instance contains those call signs monitored by this instance. Next, we explain the monitoring phase for each actor-based monitoring system in more detail.

- `monitor-indexing` - the monitoring phase includes one actor with a single monitor object of type `sfdpsOrderMultiMonitor_indx` that checks for all the events in the input sequence (see Figure 4a). The monitor actor obtains event objects from the channel `events` and feeds them to the underlying monitor object by invoking its `verify` method. The monitor instance employs indexing within the monitor. In a way, the monitoring phase of this system is equivalent to directly using the Daut tool which processes the trace sequentially.

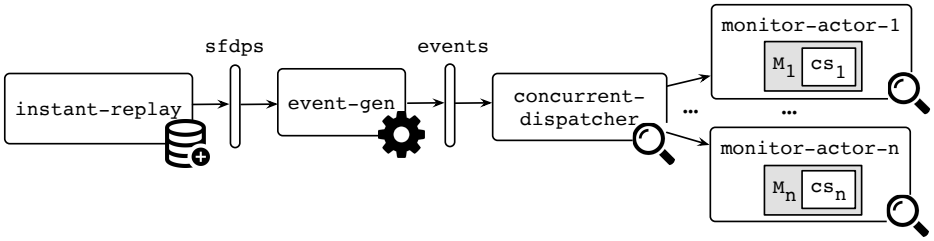
- `dispatcher-indexing` - the monitoring phase includes a dispatcher actor (of type `gov.nasa.mesa.dispatchers.IndexingDispatcher`) which creates monitor instances of type `sfdpsOrderMultiMonitor` on-the-fly, and feeds them with incoming events. The dispatcher generates one monitor instance per call sign (see Figure 4b). It stores the monitor instances in a hash map (of type `scala.collection.mutable.HashMap`), using call signs as entries to the hash map. Thus, in this system indexing is applied inside the dispatcher actor, and not inside the monitor instances. The dispatcher obtains event objects from the channel `events`, and starting with an empty hash map, for each



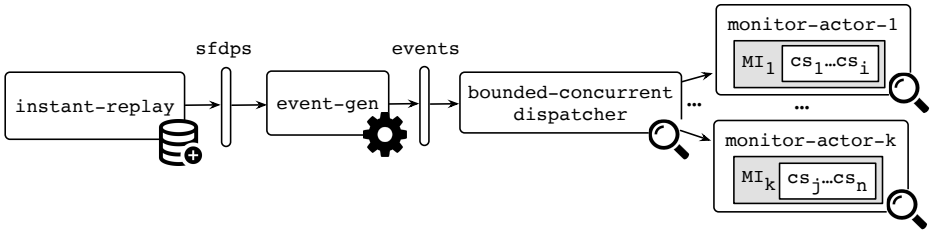
(a) *System 1:* `monitor-indexing`



(b) *System 2:* `dispatcher-indexing`



(c) *System 3:* `concurrent`



(d) *System 4:* `bounded-concurrent`

Figure 4: *Actor-based monitoring systems used in the experiment*

new call sign, adds a new monitor instance to the hash map. Moreover, for an event object with the call sign $\texttt{cs}_\texttt{i}$, the monitor actor invokes the `verify` method of the monitor instance $\texttt{M}_\texttt{i}$.

- `concurrent` - the trace analysis is performed concurrently by employing one monitor actor per call sign (see Figure 4c). Each monitor actor includes a monitor instance of type `sfdpsOrderMultiMonitor`. The runtime verification phase includes a dispatcher actor (of type `gov.nasa.mesa.dispatchers.ConcurrentDispatcher`) that obtains the event objects from the channel `events`, and for each new call sign, it generates a monitor actor on-the-fly. The dispatcher actor uses indexing by storing the references of the monitor actors in a hash map (of type `scala.collection.mutable.HashMap`) using call signs as entries to the hash map. For an event object with the call sign $\texttt{cs}_\texttt{i}$, the dispatcher then forwards the event object to the associated actor,

`monitor-actor-i`, using the point-to-point communication paradigm. Then the monitor actor invokes the `verify` method on its underlying monitor instance. For an event object of type of `TrackCompleted` which indicates the end of the flight, the dispatcher also sends a termination request to the monitor actor.

- `bounded-concurrent` - the monitoring phase is similar to the monitoring phase in the `concurrent` system, except there is a limit on the number of monitor actors generated. Therefore, one monitor actor could be associated with more than one call sign. Moreover, monitor actors contain instances of type `sfdpsOrderMultiMonitor_indx` which employs indexing inside the monitor instance. This system also uses the dispatcher actor of type `gov.nasa.mesa.dispatchers.ConcurrentDispatcher` with the key `actor-monitor-count` set to the maximum number of monitor actors in the configuration file.

Table 5 summarizes the main features of these monitoring systems which are key to the experiment.

	monitor indx	dispatcher indx	concurrency
monitor-indexing	✓	×	×
dispatcher-indexing	×	✓	×
concurrent	×	✓	✓
bounded-concurrent	✓	✓	✓

Figure 5: *The main features of the MESA monitoring systems presented in Figure 4*

3.1 Configurations

In order to build the monitoring systems illustrated in Figure 4, one needs to specify the actors and the way they are connected in configuration files in the HOCON format [15] which is a JSON dialect. MESA receives the configuration file as an input and generates the actor-based system accordingly. As an example, see Figure 6 which shows the input configuration file used to build the `bounded-concurrent` monitoring system. You can find the one-to-one correspondence between the actors specified within the `actors` block in the configuration file and the actors in Figure 4d. The dispatcher type `SfdpsConcurrentDispatcher` extends the type `ConcurrentDispatcher` towards SFDPS messages.

4 Performance Measurement of Actors

In the experiment, first, we measure the overall performance of MESA using different MESA monitoring systems. To investigate the underlying factors behind run time results further, we also measure different performance parameters for individual dispatcher and monitor actors in the monitoring system. This section explains how these parameters are measured.

```
actors = [
  { name = "instant-replay"
    class = "gov.nasa.mesa.dataAcquisition.InstantReplayActor"
    write-to = "sfdps"
    reader = {
      class = ".archive.TextArchiveReader"
      pathname = ${mesa.data}"/sfdps.xml.gz"
      buffer-size = 32768
    }
  },

  { name = "event-gen"
    class = "gov.nasa.race.actor.TranslatorActor"
    read-from = "sfdps"
    write-to = "events"
    translator = {
      class = "gov.nasa.race.air.translator.FIXM2FlightObject"
    }
  },

  { name = "bounded-concurrent-dispatcher"
    class = "gov.nasa.mesa.dispatchers.nextgen.SfdpsConcurrentDispatcher"
    read-from = "events"
    actor-monitor-count = 250
    monitor = {
      name = "sfdps-order-monitor"
      monitor-actor-class = "gov.nasa.mesa.core.MonitorActor"
      monitor-object.class =
          "gov.nasa.mesa.nextgen.monitors.sfdpsOrderMultiMonitor_indx"
      sub-monitor-count = 2000
    }
  }
]
```

Figure 6: *The configuration file specifying the* `concurrent-bounded` actor-based monitoring system

The performance parameters that we consider are the average service time, the average wait time for messages in the actor's mailbox, and the average size of actor's mailbox queue obtained after enqueuing a message. Figure 7 illustrates the relevant points at which we record data to measure the actors performance metrics. The interesting points are when a message is enqueued into and dequeued from the mailbox queue, and when the actor starts processing and finishes processing a message. The relevant data recorded at these points are stored in data containers (See Figure 8) which are defined as `case` classes and published to the Akka publish-subscribe `EventStream` channel. We also implement an actor called `stat-collector` which is subscribed to `EventStream`, and collects `MailboxStats` and `MsgProcessingStats` data containers and processes them into statistics. First, we explain how the actors performance parameters are measured in MESA.

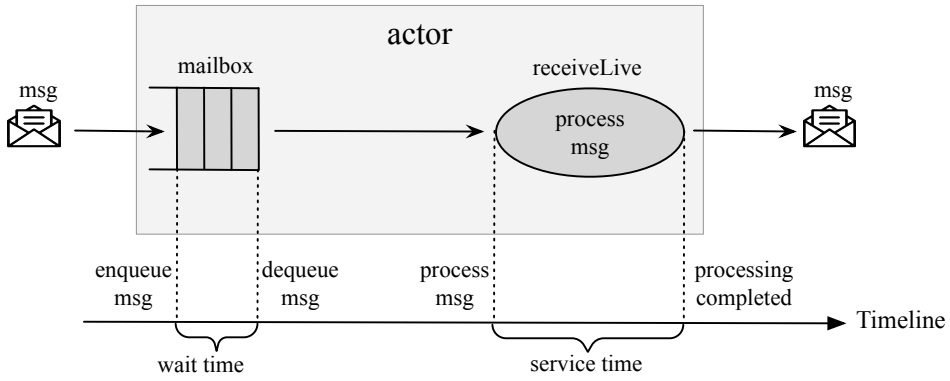


Figure 7: *The timeline for a message sent to the actor*

```
case class MsgProcessingStats(self: ActorRef, sender: ActorRef, entryTime: Long,
    exitTime: Long)
case class MsgEntryStats(queueSize: Int, receiver: ActorRef, entryTime: Long,
    envelope: Envelope)
case class MailboxStats(queueSize: Int, receiver: ActorRef, sender: ActorRef,
    entryTime: Long,
  exitTime: Long)
```

Figure 8: *Data containers used to store data processed by the* `stats-analyzer` actor

4.1 **Measuring Service Time**

Extended from RACE actors, the default behavior of MESA actors is defined by the method `receiveLive` which is of type of `PartialFunction[Any, Unit]` and processes the incoming messages. To measure the service time, we implement the type `InstrumentedReceive`, shown in Figure 9. `InstrumentedReceive` extends `PartialFunction[Any,Unit]`, and has constructor parameters of type of `PartialFunction[Any,Unit]` (called `delegatee`) and `MesaActor`. `InstrumentedReceive` overrides the `apply` method with an implementation that invokes `delegatee` on the incoming message and records the time before and after invoking `delegatee`. It then creates a data container of type `MsgProcessingStats`, and publishes it to the `EventStream` channel (by invoking `forwardStats` on the given `MesaActor`). `MsgProcessingStats` objects which are collected by `stat-collector` include the identity of the actor processing the message and the sender actor, and the time before and after processing the message.

Every MESA actor has the boolean property `stats.service` which is `false` by default. If set to `true` in the configuration file, when initializing the actor, MESA replaces the `receiveLive` with a new instance of `InstrumentedReceive` using the actor's `receiveLive` object and reference as its constructor parameters.

```
class InstrumentedReceive (val delegatee: PartialFunction[Any,Unit], val actor:
    MesaActor)
  extends PartialFunction[Any,Unit] {
  override def apply(msg: Any): Unit = {
    if (msg.isInstanceOf[RaceSystemMessage]) delegatee(msg)
    else {
      val start = System.currentTimeMillis
      delegatee(msg)
      val end = System.currentTimeMillis
      val stats = MsgProcessingStats(actor.self, start, end)
      actor.forwardStats(stats)
    }
  }

  def isDefinedAt(x: Any): Boolean = delegatee.isDefinedAt(x)
}
```

Figure 9: `InstrumentedReceive` replaces the `receiveLive` function in MESA actors to measure the service time

4.2 **Measuring Mailbox Metrics**

The approach that we used to collect mailbox data is similar to the one proposed in Chapter 16 of [4]. To obtain information from actors mailboxes, we implement a new mailbox that extends the default mailbox implementation in Akka. Akka allows for specifying the actor's mailbox in the configuration file. If no mailbox is specified for an actor, the default mailbox is used. Creating a new Akka mailbox requires a queue implementation of type `MessageQueue`, and a factory class of type `MailboxType` to instantiate the queue for corresponding actors. My mailbox implementation includes the class `StatsQueue` that extends `MessageQueue` and implements the mailbox queue. It also includes the mailbox factory class `StatsMailboxType` that extends `MailboxType`, and it is used to instantiate `StatsQueue`.

The `StatsQueue` class has a final field `queue` of type `java.util.concurrent.ConcurrentLinkedQueue` which stores the messages that are waiting in the mailbox. The two key methods which are declared in `MessageQueue` and implemented in `StatsQueue` are `enqueue` and `dequeue`. These methods are used to enqueue the message into the actor mailbox and dequeue the next message from the mailbox to be processed by the actor, respectively. The method `enqueue` creates a data container of type `MsgEntryStats`, and adds it to the end of `queue`. `MsgEntryStats` (see Figure 8) stores the original message, encapsulated by an `Envelope` object in Akka, along with the size of the mailbox queue, the receiver actor identity, and the message entry time into the queue.

The method `dequeue` obtains the next `MsgEntryStats` from `queue`, and creates a data container of type `MailboxStats` and publishes it to `EventStream`. It also returns the original message of type `Envelope` to the actor for processing. `MailboxStats` (see Figure 8) includes the size of the queue after the message

entered the mailbox, the identities of the receiver and sender actors, and the message entry time to and the exit time from the mailbox queue. Using this information for every message in the actor's mailbox, `stat-collector` computes the average wait time for a message in the actor's mailbox. It also computes the average of the mailbox size recorded when enqueueing messages. Note that this does not exactly reflect the average size of the mailbox since it does not take into account the mailbox changes in between enqueues which can stay empty for a while. Therefore, we refer to it as average *sampled* mailbox size.

The new mailbox type is defined in the configuration file by adding the following lines in the configuration file.

```
stats-collector-mailbox {
  mailbox-type = "gov.nasa.mesa.reporting.stats.StatsMailboxType"
}
```

Every MESA actor has the boolean property `stats.mailbox` which is `false` by default. If that is set to `true` in the configuration file, when creating the actor, MESA uses `StatsQueue` for the actor's mailbox implementation instead of the default one.

5 Akka Threading Model

Before presenting the experiment, we briefly explain the underlying threading model in Akka. Scheduling actors in Akka is performed by dispatchers which are low level components built into the Akka toolkit. Note that these dispatchers are completely different from the dispatchers components implemented in MESA. To avoid confusion, in some context, we refer to the ones implemented by Akka as *Akka dispatchers*. Akka dispatchers are responsible for management of actors mailboxes and the threading strategy. They push messages into actors mailboxes, and associate threads from the thread pools to actors to process messages in their mailboxes. Akka provides a fixed number of dispatchers to choose from. The user can also assign a certain Akka dispatcher to a group of actors. The built-in dispatcher types in Akka are as follows.

- `Dispatcher` is the default Akka dispatcher which associates all the assigned actors to one thread pool.
- `PinnedDispatcher` provides an actor with an exclusive access to a single thread.
- `BalancingDispatcher` redistributes messages from busy actors to the ones with empty mailboxes.
- `CallingThreadDispatcher` is only used for testing, and uses the current thread to execute any actor.

Akka provides configuration parameters to tune dispatchers to specific needs. The parameter `throughput` represents the maximum number of messages processed

by the actor before the assigned thread is returned to the pool. The parameter `throughput-deadline-time` represents the deadline for the actor to process messages each time it executes. One can also specify the underlying thread pool implementation used in the Akka dispatcher by setting its executor component using the parameter `executor`. By default, Akka uses `fork-join-executor` which relies on the *work-stealing* pattern where threads always try to find tasks from the submitted tasks to the pool and the ones created by other running tasks. Akka also includes `thread-pool-executor` which offers a dynamic thread pool that can decrease or increase in size depending on how busy or idle the threads are. Akka also allows users to implement their own customized executor.

The number of threads in the pool is another measure that can be tuned. With too few threads which may cause low CPU utilization, the actors are not able to keep up with the arrival of messages. With too many threads, the context switch time between threads increases which leaves less time for processing the threads. The Akka dispatcher configuration provides three parameters to specify the thread pool size. The parameters `parallelism-min` and `parallelism-max` represent the minimum and maximum number of threads, respectively, and `parallelism-factor` is a factor to calculate the number of threads based on available processors. The size of the thread pool is `parallelism-factor` multiplied by the number available processors. The number available processors is the value returned by the method `java.lang.Runtime.availableProcessors()` which gives the maximum number of logical cores available to the virtual machine. If the calculated thread pool size is smaller than `parallelism-min` or larger than `parallelism-max` then the thread pool size becomes `parallelism-min` or `parallelism-max`, respectively. Moreover, to set the thread pool size to a specific value, one could set both `parallelism-min` and `parallelism-max` to that value.

We use the default Akka dispatcher setting in the experiment which is as follows. All actors use the `Dispatcher` implementation with the default value 5 for `throughput`, 0 for `throughput-deadline-time` which indicates no time limit, and `fork-join-executor` for the executor. Moreover, `parallelism-min` and `parallelism-max` are set to 8 and 64, and `parallelism-factor` is set to 3.

6 Experiment

The experiment is divided into two parts. The first part, presented in Section 6.2, evaluates the overall performance of the different MESA actor-based systems presented in Section 3. The second part, presented in Section 4, evaluates the performance of individual dispatcher and monitor actors.

6.1 Setup

The experiment is performed on an Ubuntu 18.04.3 LTS machine with 31.1 GB of RAM and 10 Intel®Xeon®W-2155 processors with a base frequency of 3.30 GHz and hyper-threading which provides 20 threads ($2\times$ number of cores). The initial Java heap size and the maximum Java heap size, represented by the Xms and Xmx JVM parameters, are set to 12 GB. Moreover, the time is measured using

`java.lang.System.nanoTime()`.

For all the runs in this experiment, we use an archive including recorded SFDPS messages as an input. We evaluate the MESA systems against an input trace, `T`, including 200,000 messages where each message corresponds to an event of type `FlightState` or `TrackCompleted`. `T` includes data from 3215 different flights. Therefore, the value of `n` in Figure 4) is 3215. The number of sub-monitors in `sfdpsOrderMultiMonitor` and `sfdpsOrderMultiMonitor_indx` is set to 2000 in all the configurations. Moreover, the value returned by `java.lang.Runtime.availableProcessors()` is 20 where with `parallelism-factor` set to 3, the size of the thread pool for `Dispatcher` (the default Akka dispatcher) becomes 60.

6.2 System Performance

To evaluate the overall performance of the actor-based monitoring systems presented in Section 3, using a bash script, each system is executed 10 consecutive times. The average time of the 10 runs used to process the input trace `T` for the monitoring systems `monitor-indexing`, `dispatcher-indexing`, `concurrent`, and `bounded-concurrent` are compared in Figure 10. Note that the legend `bcon` in the graphs stands for `bounded-concurrent` followed by the number of monitors.

Considering the 3215 different call signs in `T`, `monitor-indexing` includes one monitor actor which contains one monitor object that tracks all 3215 flights. The `dispatcher-indexing` system creates one actor that contains a hash map including 3215 monitor objects where each monitor object handles messages from one flight. The `concurrent` monitoring system creates 3215 monitor actors on-the-fly where each monitor actors handles messages from one flight. The `bounded-concurrent` monitoring system creates 250 monitor actors where each monitor actor tracks 12 to 13 call signs.

The results show that `monitor-indexing` exhibits the worst performance followed by the `dispatcher-indexing` monitoring system. The discrepancy between the run time for these two monitoring systems reveals that applying indexing at the dispatcher level is more efficient that indexing within the monitor. The results also show that `bounded-concurrent` exhibits the best performance, being slightly faster than the `concurrent` monitoring system. Table 1 includes ratios that compare the run times for the input trace `T`.

	$\frac{monitor-indexing}{dispatcher-indexing}$	$\frac{dispatcher-indexing}{concurrent}$	$\frac{concurrent}{bounded-concurrent}$
ratio	1.78	2.63	1.22

Table 1: *Performance ratios comparing different MESA systems*

To investigate the contributing factors behind different run times closer, we run each MESA system in Figure 10 once along with VisualVM which is a Java profiler that provides a visual interface to monitor CPU utilization, garbage collector activities, memory usage, and heap data. Figure 11 shows the CPU usage which represents the percentage of total computing resources in use during the run.

It can be seen that the CPU utilization for `monitor-indexing` is mostly under 30%, and for `dispatcher-indexing` is mostly between 30% and 60%. These

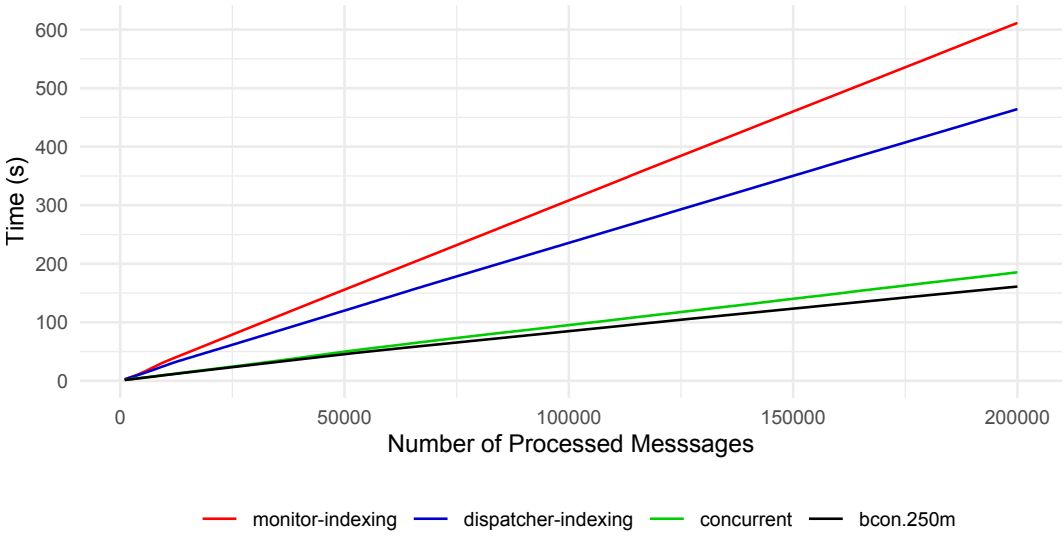
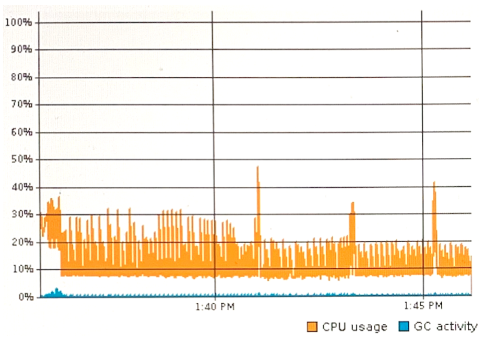
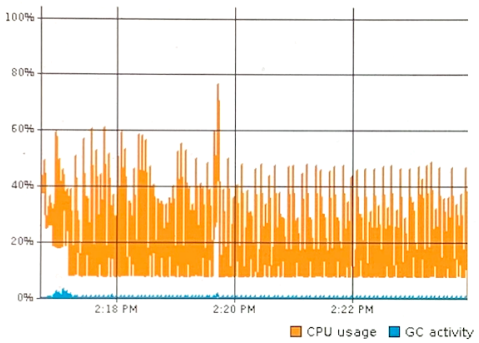


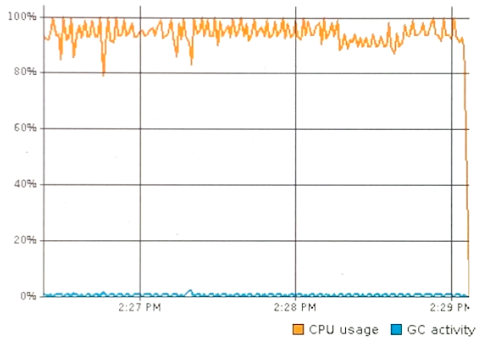
Figure 10: *Comparing the run times of different MESA actor systems*



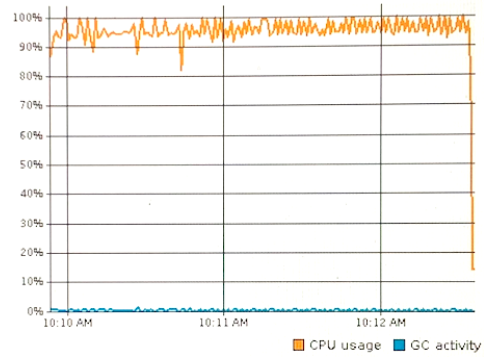
(a) `monitor-indexing`



(b) `dispatcher-indexing`



(c) `concurrent`

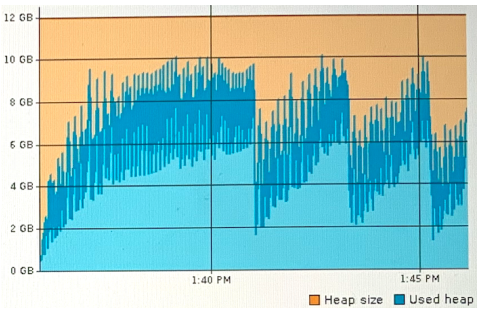


(d) `bounded-concurrent` using 250 monitor

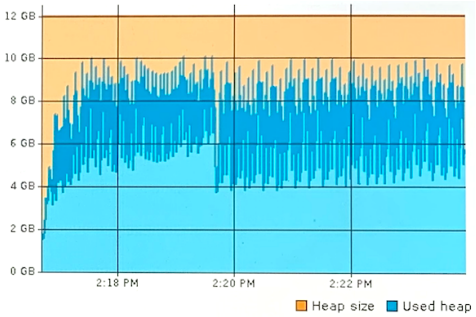
Figure 11: *The CPU usage profiles obtained by VisualVM*

amounts are significantly lower than the CPU utilization for the `concurrent` and `bounded-concurrent` monitoring systems which is mostly above 90%. The main reason is that `monitor-indexing` and `dispatcher-indexing` use a single actor in the monitoring phase which processes messages sequentially and therefore, they do not take advantage of available cores. Whereas, `concurrent` and `bounded-concurrent` use concurrent actors in the monitoring phase. In general, increasing the number of concurrent monitor actors increases the CPU utilization which can lead to a better performance. However, increasing the number of concurrent actors also comes with additional overhead including increase in context-switching between actors which could slow down the system.

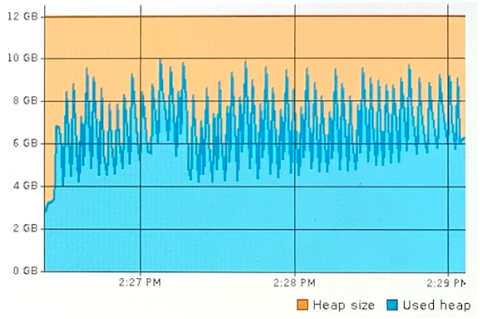
It can be seen that in Figure 11, the CPU utilization profile for all the systems goes down before the system terminates. Once the input trace `T` is fully processed, a termination request is sent to all the live actors in the system by the master actor. The systems with higher number of actors could take longer to shutdown. The run time reported in these experiments is from the start of the run to the point that the system is processed the entire input trace, before the termination mechanism is even triggered. Therefore, the termination process does not influence the results.



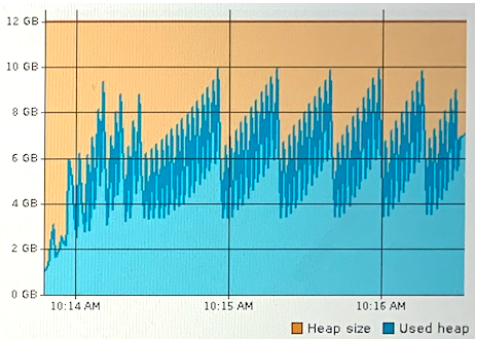
(a) `monitor-indexing`



(b) `dispatcher-indexing`



(c) `concurrent`



(d) `bounded-concurrent` (250 monitors)

Figure 12: *The heap data profiles obtained by VisualVM*

Figure 12 shows the heap data for each system obtained from VisualVM. The spikes in the profiles are indicative of short living objects collected during a garbage collection cycle which are the messages exchanged between actors in these runs. It can be seen that the heap data consumption for all the runs is below 10G.

Note that in a way the `concurrent` monitoring system can be seen as a special case of `bounded-concurrent` where the maximum number of monitors to be created is equal to the number of call signs. Figure 13 compares `concurrent` with the `bounded-concurrent` where the maximum number of monitor actors is set to 3215. It can be seen that the `bounded-concurrent` system is slower. That is due to two reasons. The extra work that goes to maintaining the groups of monitor actors in the case of `bounded-concurrent` can cause overhead. Moreover, in `bounded-concurrent`, indexing is applied inside the monitor objects, and since only one call sign is assigned to each monitor instance, the monitor indexing does not improve the performance and causes additional overhead.

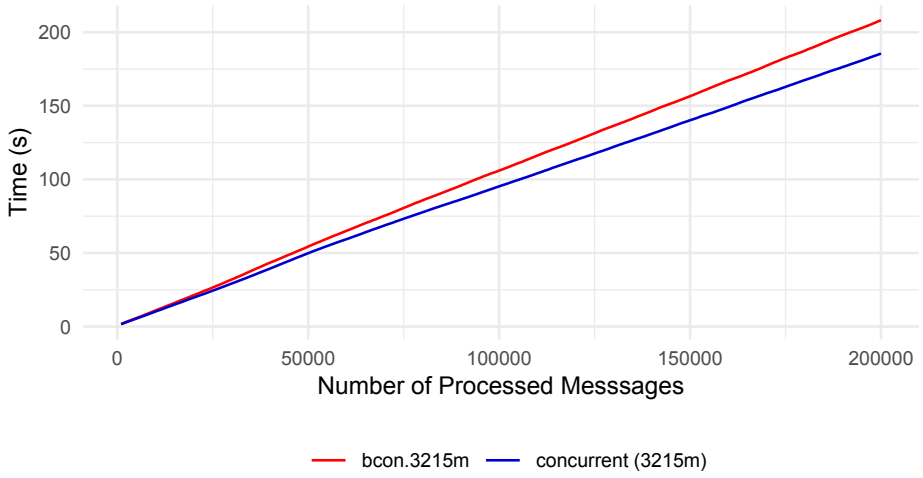


Figure 13: `concurrent` versus `bounded-concurrent`

To see how the number of monitor actors impact the run time, we compare the `bounded-concurrent` run times with different numbers of monitor actors, including 125, 250, 500, 1000, 2000, and 3215 actors. Note that increasing the number of monitor actors imposes less load on each monitor actor. The number of flights tracked by each monitor actors for the systems with 125, 250, 500, 1000, 2000, and 3215 monitor actors is 25-26, 12-13, 6-7, 3-4, 1-2 (with majority 2), and 1 flight, respectively. The average of 10 runs for these systems are compared in Table 2 and in Figure 14.

It can be seen that the system performs best with 250 monitor actors, and from there as the number of monitor actors increases the run time increases. The results also show that the system with 125 monitor actors is slightly slower than the system

with 250 monitor actors. As mentioned earlier, increasing the number of monitor actors decreases the load on individual monitor actors, however, it increases overheard from creating and maintaining more actors.

#monitors	125m	250m	500m	1000m	2000m	3215m
time (s)	169	161	167	169	183	208

Table 2: *Comparing the run times of different MESA actor systems*

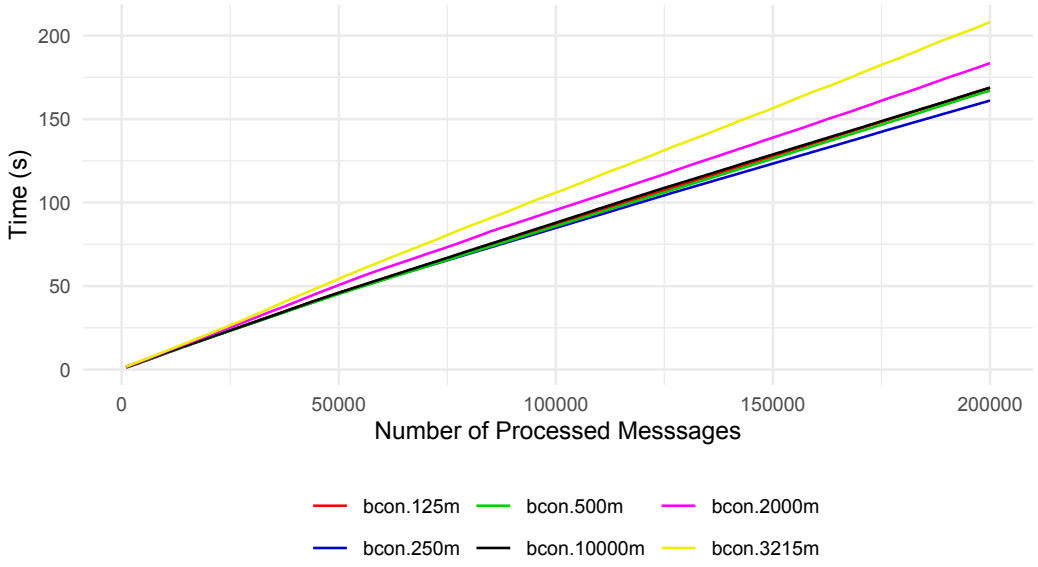
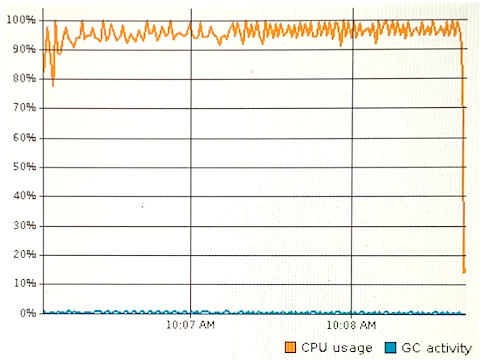
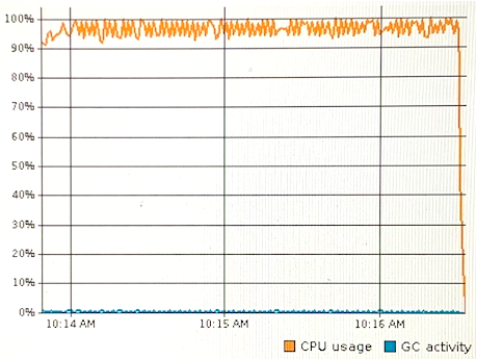


Figure 14: *The* `bounded-concurrent` run times with different number of monitor actors

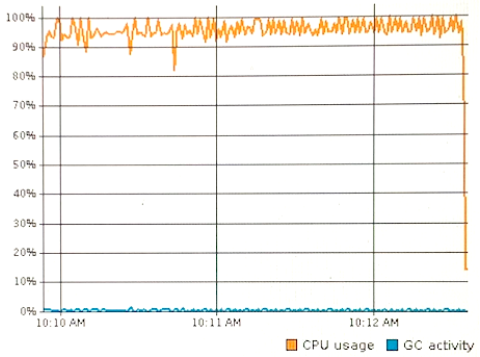
Using VisualVM, we obtain the CPU utilization and the heap data profiles for the MESA systems presented in Figure 14. Figure 15 illustrates the CPU utilization profiles for the same systems. It can be seen that in all cases the `bounded-concurrent` system maintains a high CPU utilization which is mostly over 90%. Figure 16 illustrates the heap data profiles. It can be seen that there there are not many discrepancies between the heap profiles as well.



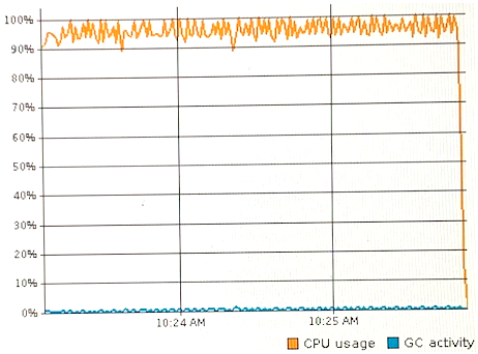
(a) `bounded-concurrent` (125 monitors)



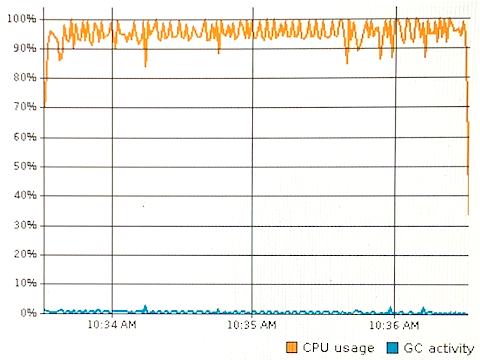
(b) `bounded-concurrent` (250 monitors)



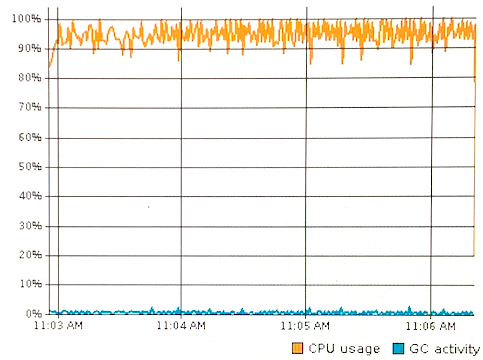
(c) `bounded-concurrent` (500 monitors)



(d) `bounded-concurrent` (1000 monitors)

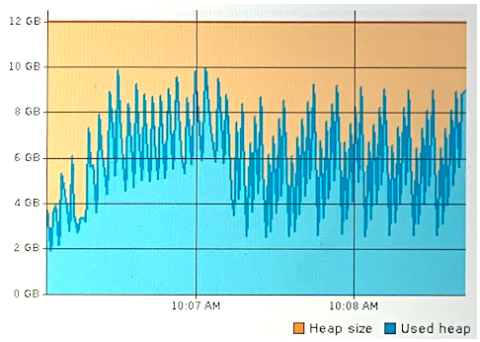


(e) `bounded-concurrent` (2000 monitors)

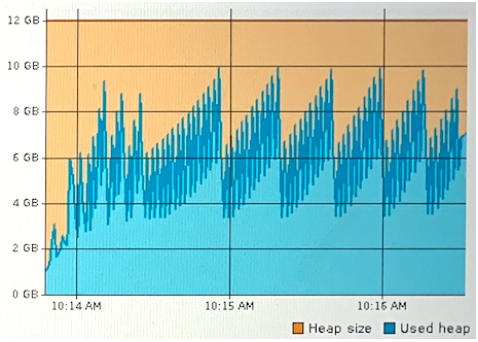


(f) `bounded-concurrent` (3215 monitors)

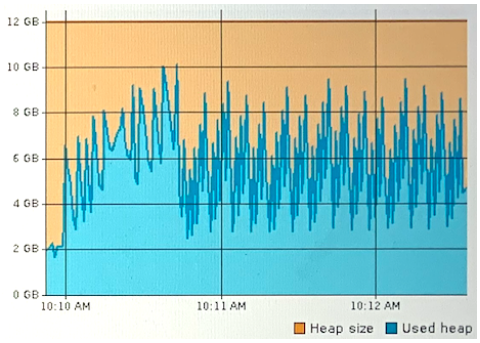
Figure 15: *The CPU utilization profiles for* `bounded-concurrent`



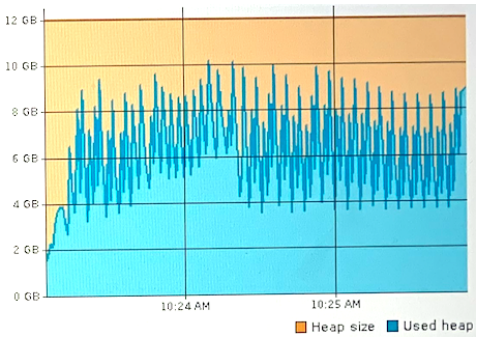
(a) `bounded-concurrent` (125 monitors)



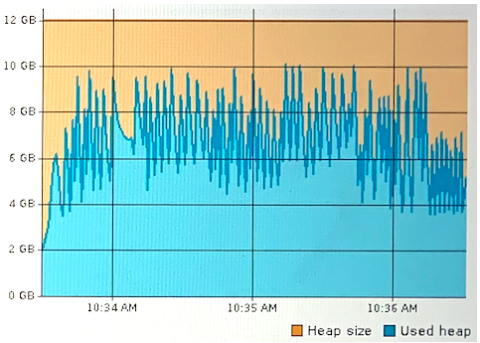
(b) `bounded-concurrent` (250 monitors)



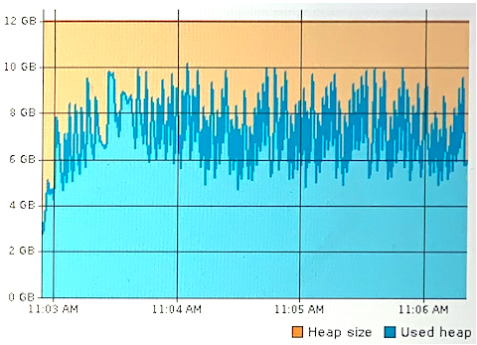
(c) `bounded-concurrent` (500 monitors)



(d) `bounded-concurrent` (1000 monitors)



(e) `bounded-concurrent` (2000 monitors)



(f) `bounded-concurrent` (3215 monitors)

Figure 16: *The VisualVM heap data profiles for* `bounded-concurrent`

6.3 Actors Performance Analysis

This section shows the results for individual actors in the monitoring systems using the features explained in Section 4, which are referred to as *ASF* (stands for actor statistics features) from now on. To activate ASF, the properties `stats.mailbox` and `stats.service` are set to `true` for dispatcher and monitor actors. Moreover, the `stat-collector` actor is added to the actor system by adding the following block to the configuration file. The experiment presented is this section is also

```
{
  name = "stat-collector"
  class = "gov.nasa.mesa.reporting.stats.StatCollector"
  output-path = "path/to/stat-collector/results"
}
```

conducted on the Ubuntu machine and uses the inputs and settings presented in Section 6.1. Before presenting the results for individual actors, we show the overhead from activating ASF.

6.3.1 *ASF Overhead*

Figure 17 compares the runtime of the different MESA systems with and without ASF. Note that the postfix `asf` in all the graphs represents runs with ASF activated. It can be seen that all the monitoring systems presented in Figure 17 slow down with ASF activated. Moreover, comparing the overheads reveals that the `monitor-indexing` system exhibits the largest overhead from activating ASF. Note that in the `monitor-indexing` system, ASF is only activated for one monitor, whereas, for `concurrent` and `bounded-concurrent`, ASF is activated for the dispatcher and all the monitor actors. Therefore the overall overhead in these systems is larger since there are more messages exchanged between the actors and `stat-collector`.

Figure 18 and 19 show the CPU usage and the heap data profiles for `monitor-indexing`, `dispatcher-indexing`, `concurrent`, and `bounded-concurrent` using 250 monitors. The results in Figure 18 reveal that activating these features increases the CPU utilization for `monitor-indexing` and `dispatcher-indexing`. The reason is that these systems have a very few actors, and one additional *runnable* actor, `stat-collector`, which always has messages in its mailbox can noticeably lift the CPU utilization. Whereas, for `concurrent` and `bounded-concurrent` which already have many actors with high CPU utilization, adding an additional actor does not raise the CPU utilization noticeably.

It can be also seen from Figure 18 that the shutdown process which is the flat part of the profile at the end becomes longer with ASF activated. The shutdown request is sent from the master actor to all the actors in the system in the form of a message that is placed in the actors mailboxes. The longer shutdown process is due to the wait on the `stat-collector` actor to process the messages waiting in its mailbox. Figure 19 shows that activating ASF leads to larger heap data in all cases. This is due to the overhead from the messages placed in the mailbox of `stat-collector`.

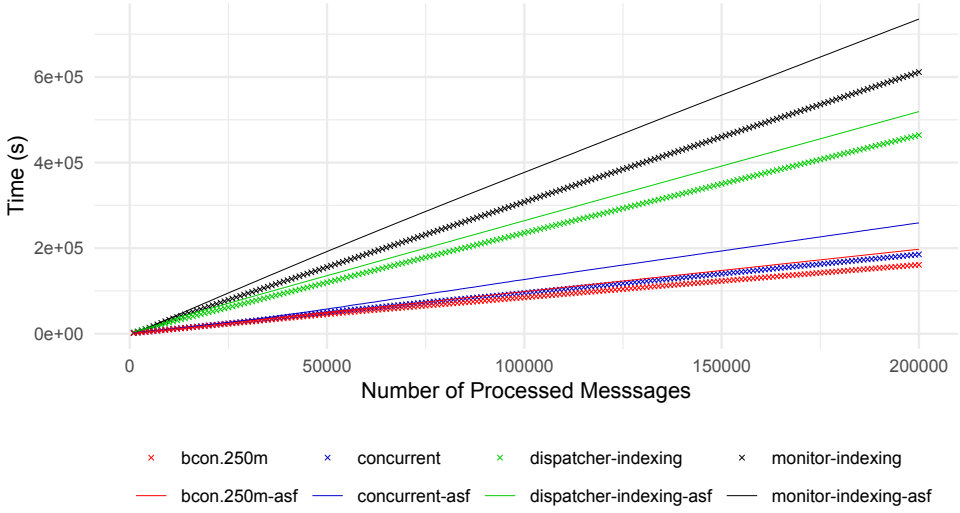
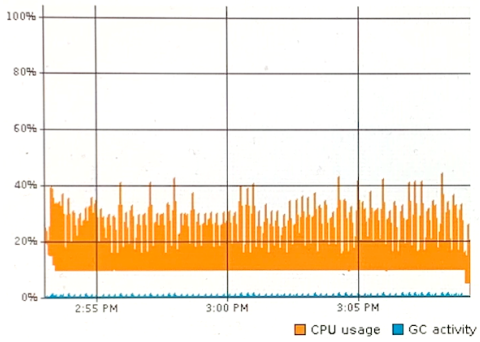
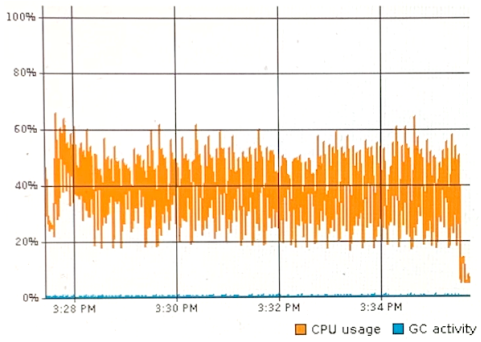


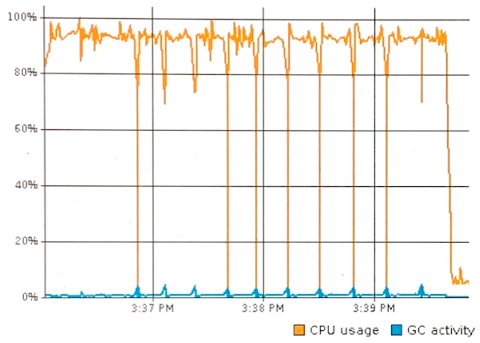
Figure 17: *Comparing MESA systems run times with and without ASF*



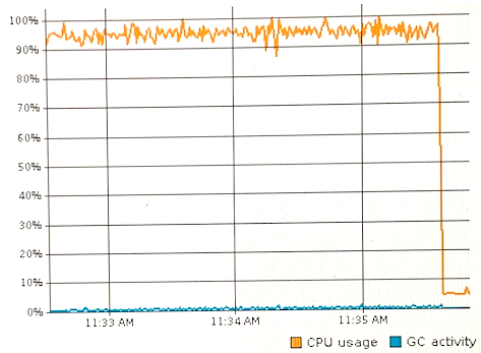
(a) `monitor-indexing` with ASF



(b) `dispatcher-indexing` with ASF

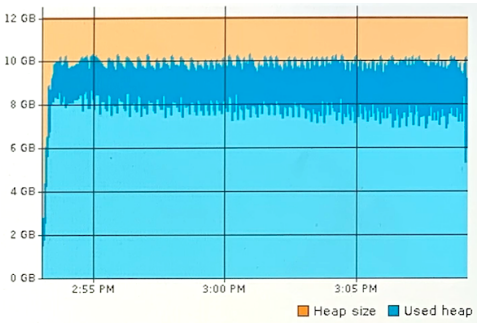


(c) `concurrent` with ASF

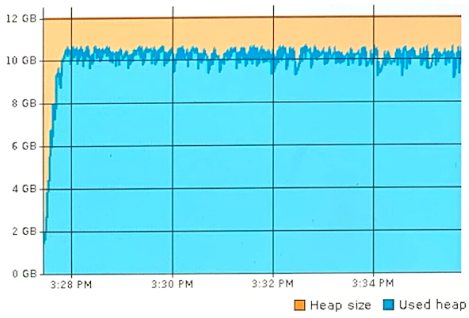


(d) `bounded-concurrent` with ASF (250 monitors)

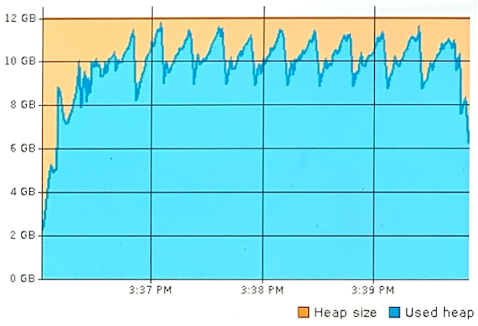
Figure 18: *The CPU utilization profiles for MESA systems with ASF activated*



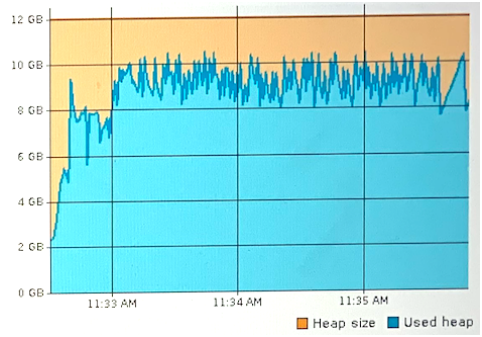
(a) `monitor-indexing` with ASF



(b) `dispatcher-indexing` with ASF



(c) `concurrent` with ASF



(d) `bounded-concurrent` with ASF (250 monitors)

Figure 19: *The heap usage profiles for the MESA systems with ASF activated*

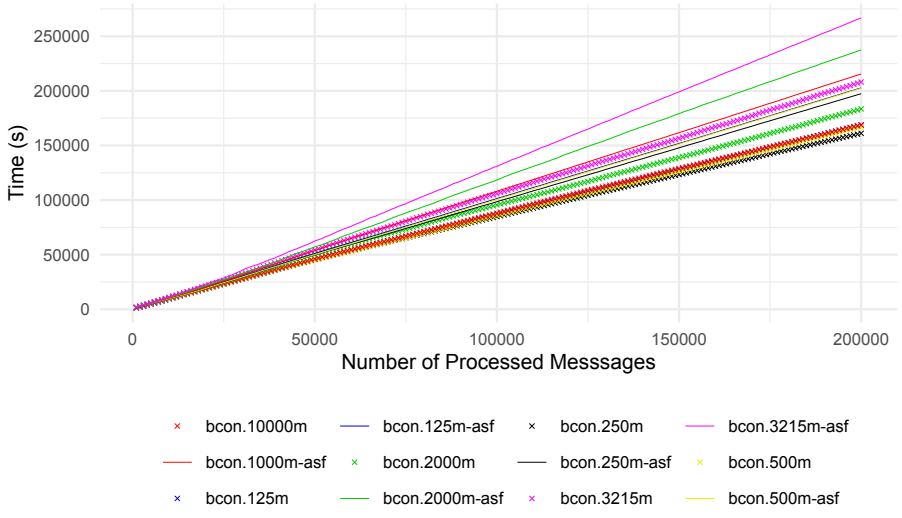


Figure 20: *Comparing the* `bounded-concurrent` runs with and without ASF

Table 3 includes the run time and overhead for `bounded-concurrent` when ASF is activated. Figure 20 compares the run times for the same MESA systems with and without ASF. It can be seen that activating ASF slows down all the runs, and the system with 250 monitor actors still gives the best performance. Moreover, Table 3 shows that in general, as the number of monitor actors increases, the overhead from ASF increases as well.

#monitors	125m	250m	500m	1000m	2000m	3215m
time (s)	203	197	202	215	237	267
ASF overhead	20%	22.5%	21.1%	27.7%	29.4%	28.1%

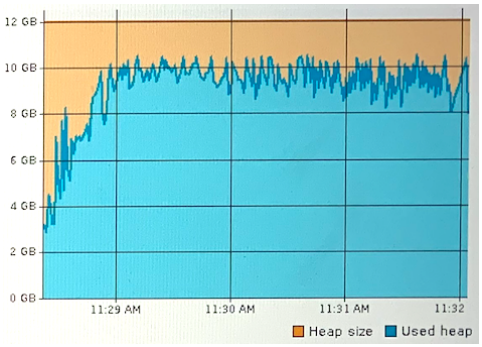
Table 3: *The run time and overhead for* `bounded-concurrent` with ASF

Figure 21 illustrates the heap data profiles for `bounded-concurrent` with 125, 250, 500, 1000, 2000, and 3215 monitors with ASF activated. Comparing the profiles with the ones illustrated in Figure 16 shows that activating ASF increases the heap data usage for all these systems. Moreover, the CPU utilization profiles for these systems show that the CPU usage stays above 90% in all cases, which is similar to the CPU usage for runs without ASF illustrated in Figure 15.

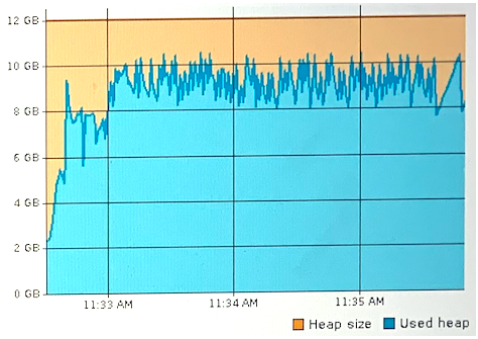
6.3.2 *Actors Performance Results*

Next, we present the results for individual actors in the monitoring systems presented in this report. Figure 22 compares the dispatcher actors parameters for the systems `monitor-indexing`, `dispatcher-indexing`. It shows the average service time, the average wait time in the mailbox queue, and the average sampled mailbox queue size for the dispatcher actor in each system. These parameters are higher for the `monitor-indexing` system, which reveals that for this particular system under observation, it is more efficient to apply indexing at the dispatcher level than applying indexing at the monitor level when using one actor in the monitoring phase. These results are also aligned with the results presented in Figure 17.

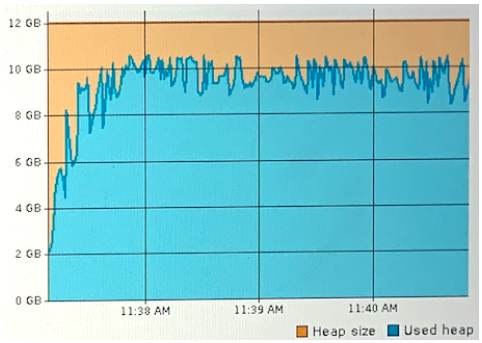
Figure 23 compares the dispatcher actors performance metrics for `bounded-concurrent` with different numbers of monitor actors. It can be seen that the average service time increases as the number of actors increases. This is aligned with the fact that using more monitor actors increases the load of the dispatcher actor since it needs to generate more monitor actors. Moreover, starting from the system with 250 monitors the average message wait time in the queue increases as the number of actors increase. This implies the longer the service time in the dispatcher actor, the longer the wait in the dispatcher mailbox. The figure shows that the average sampled mailbox size for the dispatcher actors in all cases only varies in a small range, where the queue is shorter for the dispatcher with smaller service time.



(a) `bounded-concurrent` with ASF (125 monitors)

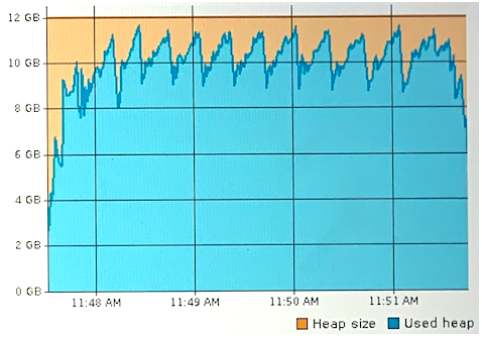


(b) `bounded-concurrent` with ASF (250 monitors)

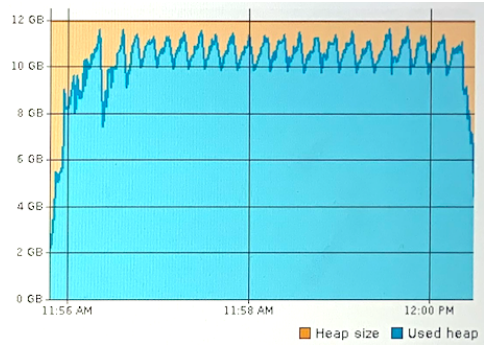


(c) `bounded-concurrent` with ASF (500 monitors)

(d) `bounded-concurrent` with ASF (1000 monitors)

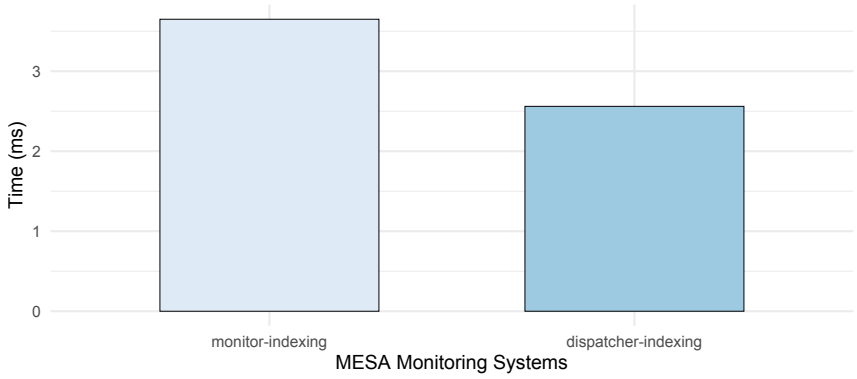


(e) `bounded-concurrent` with ASF (2000 monitors)

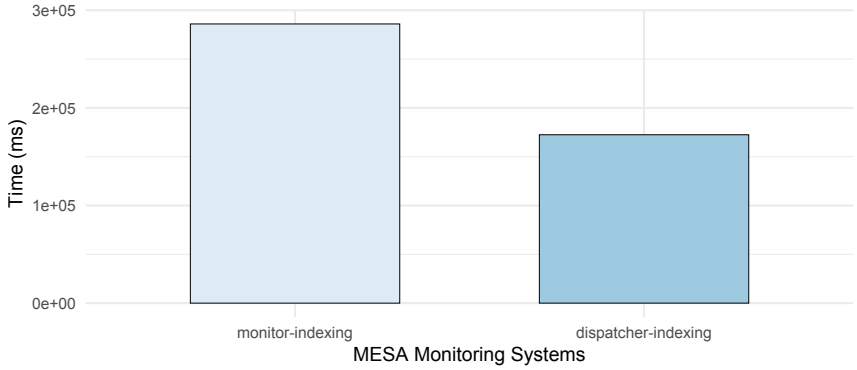


(f) `bounded-concurrent` with ASF (3215 monitors)

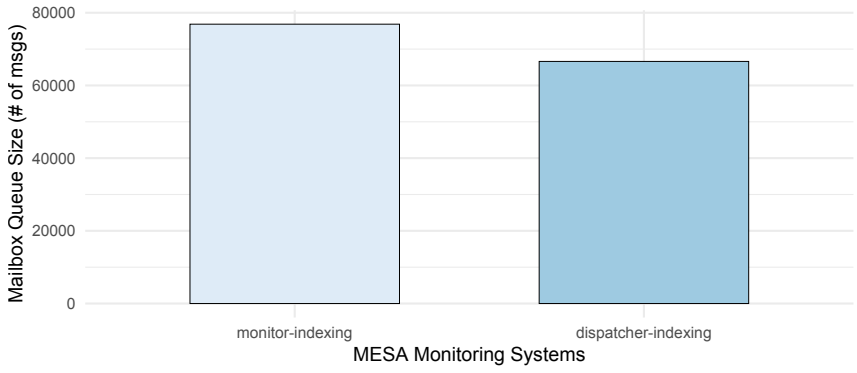
Figure 21: `bounded-concurrent` heap profiles with ASF activated



(a) *Service time*

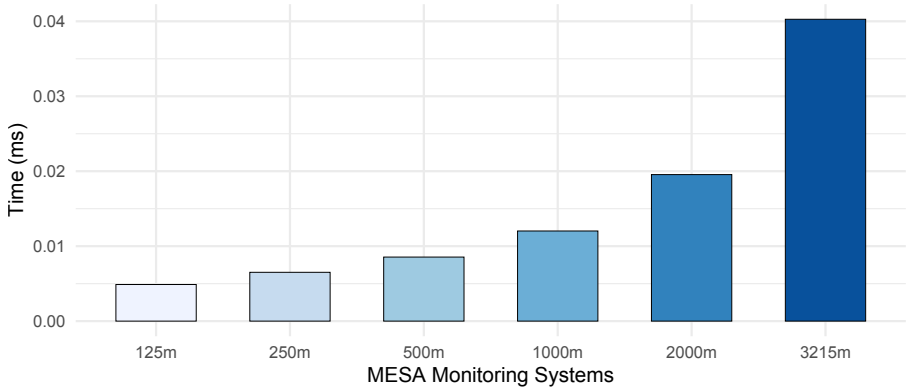


(b) *Wait time in the mailbox*

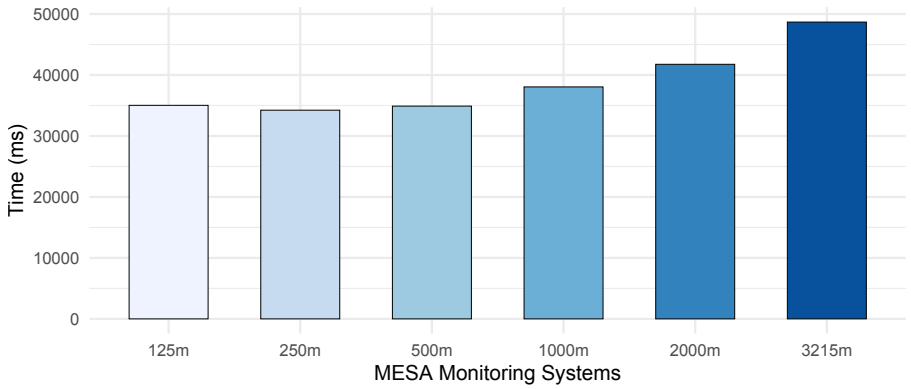


(c) *The average sampled mailbox size*

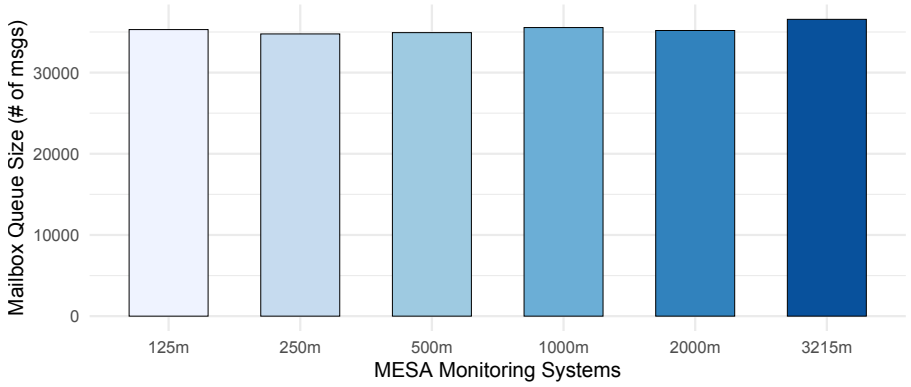
Figure 22: *Comparing the dispatcher performance metrics for the actor in the monitoring step of* `monitor-indexing` and `dispatcher-indexing`



(a) *Service time*

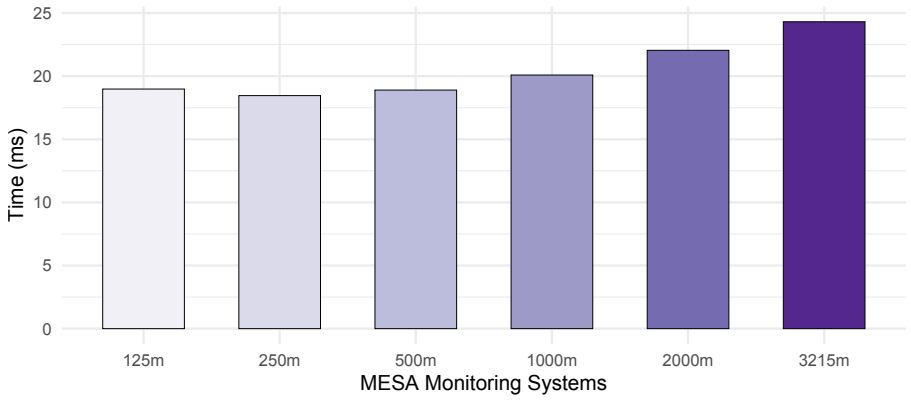


(b) *Wait time in the mailbox*

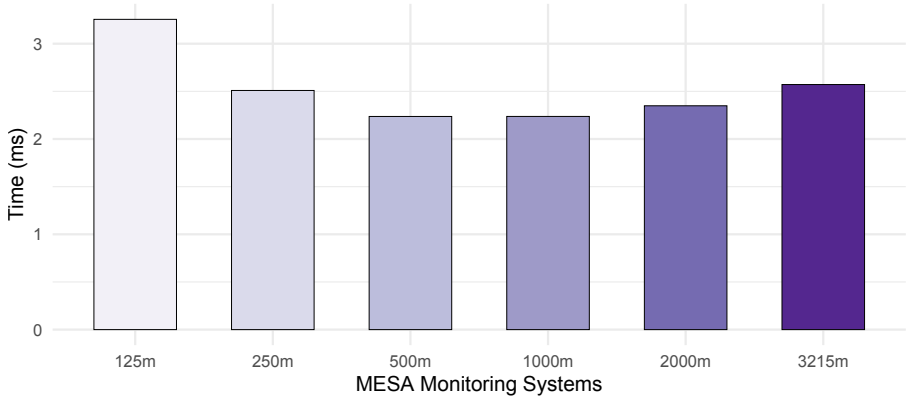


(c) *The average sampled mailbox size*

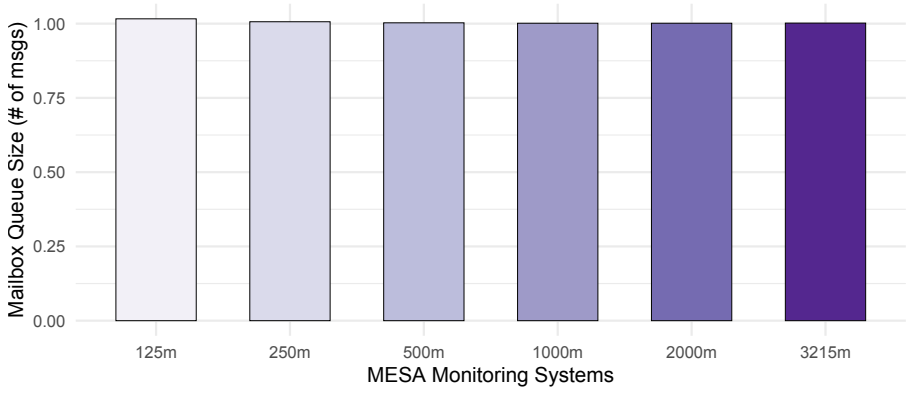
Figure 23: *Comparing the dispatcher performance metrics for* `bounded-concurrent` using different numbers of monitor actors



(a) *Service time*



(b) *Wait time in the mailbox*



(c) *The average sampled mailbox size*

Figure 24: *Comparing the monitors performance metrics for* `bounded-concurrent` using different numbers of monitor actors

Figure 24 compares the monitor actors performance metrics for `bounded-concurrent` with different numbers of monitor actors. It can be seen that starting from the system with 250 monitor actors, the average service time for monitor actors increases as the number of monitor actors increases. Decreasing the number of monitor actors increases the load on individual actors since each monitor actor deals with higher number of flights. On the other hand, applying indexing within the monitor actors helps with improving their performance, and for cases with a higher number of monitor actors, indexing within the monitor can lead to overhead as also shown in Figure 13.

The second bar graph in Figure 24 also shows that the systems with fewer monitor actors have higher average wait time in the queue. This could be due to the higher arrival rate of messages for these monitors. The last bar graph in Figure 24 shows that the average sampled mailbox size for monitor actors in all the systems is almost 1. That is, on average, every time a message is placed in the monitor actor mailbox, there is no other messages in the queue in all cases. Note that this measure does not reflect the arrival rate of messages since it does not take into account the periods where the mailboxes are empty.

7 Discussion and Conclusion

Throughout the experiment, we observed various competing sources of overhead in the MESA actor-based monitoring systems. These factors, which are as follows, need to be taken into consideration when configuring values of the related parameters.

- *Sequential processing of messages* - limiting the number of concurrent monitor actors on a multicore machine can lead to a low CPU utilization. On the other hand, increasing concurrency can increase CPU utilization. Therefore, distributing the input trace among multiple actors rather than using one single monitor actor to process the entire trace sequentially can improve the performance.

- *Actor instantiation* - there is a slight overhead associated with creating a new actor. According to Akka documentation the actor base memory overhead is roughly 300 bytes per instance.

- *Runnable actors* - runnable actors are those actors with non-empty mailbox queues which need to be scheduled to run and process their messages. Assigning actors to threads from the thread pool and context switching between them impose overhead. Therefore, the more runnable actors, the more overhead imposed.

- *Size of mailbox queues* - since MESA uses unbounded mailboxes, increase in the number of messages waiting to be processed in the actor's mailbox increases the heap data, and depending on the JVM heap size this could lead to more frequent garbage collector cycle. Garbage collection consumes

CPU resources which can limit the CPU resources that go to running the monitoring system and therefore, it slows it down.

The combination of these factors can make one MESA system perform better than the other one. As shown earlier in Figure 10, the `bounded-concurrent` system with 250 monitors performs the best. This shows that for this particular system under observation, the competing factors outlined above lead to an optimal performance when using 250 concurrent monitors.

Note there are various challenges associated with microbenchmarking on JVM that can impact accuracy of the results when dealing with smaller time measures such as service time and wait time for messages in the actor mailboxes. To address this issue one could employ tools such as JMH to provide more accurate benchmarking [16].

The main conclusion from the experiments is that concurrency can improve the performance of a monitoring system considerably. Moreover, due to competing overhead sources, there is an optimal number of concurrent monitors. Given the system under observation, there is no clear way to find the optimal number of concurrent monitor actors upfront. What MESA provides is a platform that can facilitate the processing of finding that optimal number. It provides building blocks for monitoring systems which are highly configurable. One can easily tweak these parameters in the configuration file to observe and study different runs. MESA can be also used to determine the number of concurrent monitor actors dynamically.

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