TEEMon: A continuous performance monitoring framework for TEEs

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Abstract

Trusted Execution Environments (TEEs), such as Intel Software Guard eXtensions (SGX), are considered as a promising approach to resolve security challenges in clouds. TEEs protect the confidentiality and integrity of application code and data even against privileged attackers with root and physical access by providing an isolated secure memory area, i.e., enclaves. The security guarantees are provided by the CPU, thus even if system software is compromised, the attacker can never access the enclave’s content. While this approach ensures strong security guarantees for applications, it also introduces a considerable runtime overhead in part by the limited availability of protected memory (enclave page cache). Currently, only a limited number of performance measurement tools for TEE-based applications exist and none offer performance monitoring and analysis during runtime.

This paper presents TEEMon, the first continuous performance monitoring and analysis tool for TEE-based applications. TEEMon provides not only fine-grained performance metrics during runtime, but also assists the analysis of identifying causes of performance bottlenecks, e.g., excessive system calls. Our approach smoothly integrates with existing open-source tools (e.g., Prometheus or Grafana) towards a holistic monitoring solution, particularly optimized for systems deployed through Docker containers or Kubernetes and offers several dedicated metrics and visualizations. Our evaluation shows that TEEMon’s overhead ranges from 5% to 17%.

1 Introduction

Cloud computing is a popular way to deploy modern online services since it lets users focus on their applications by delegating tasks like resource management to the cloud provider. In such multi-tenant environments, users care about protecting their data and applications, especially under the threats of powerful adversaries with root privileges or even physical access to machines. As such, users cannot rely on OS access control mechanisms (bypassed by the former), or on process/memory isolation (bypassed by the latter, for instance via cold-boot attacks [43]). In this context, cloud users have to ensure their data is always protected: at rest, in transit over the wire, and while being processed in the main memory.

To overcome these issues, hardware-assisted Trusted Execution Environments (TEEs) such as Intel SGX [24, 54], ARM TrustZone [75], IBM SecureBlue++ [29, 74], and AMD SEV [44] offer a practical approach to protect their services in an untrusted cloud [56]. The TEE technologies provide strong integrity and confidentiality guarantees regardless of the trustworthiness of the underlying software (e.g., the operating system or the hypervisor). Recently, Intel SGX has become available in the cloud [22, 45], unleashing a plethora of services to be ported, including data processing systems such as MapReduce [67], coordination services [31], content-based routing [58] and databases [60, 66]. Legacy services can also be executed with Intel SGX without any modification by using frameworks [25, 70] that transparently shield existing applications.

While promising at first glance, the approach of leveraging TEEs suffers from several technical issues, especially regarding performance overhead. Indeed, legacy applications running inside secure isolated areas of the hardware, called enclaves, suffer from significant performance issues [25, 73]. From the cloud user’s vantage point, they require strong security guarantees for the code and data of their applications, as well as low runtime overhead. Gjendrum et al. [35] proposed a set of guidelines for better enclave performance in a cloud environment recommending small enclave page cache (EPC) sizes of 64 kB and minimizing ECALL arguments for faster transitions. Several studies [25, 31, 73] identified costly EPC paging and enclave transitions as major SGX performance bottlenecks. While solutions exist to mitigate this issue (e.g., Switchless [68], HotCalls [46]), performing a context switch from the inside to the outside of enclaves still introduces a significant overhead since the hardware needs to prevent the context switch from revealing any sensitive data stored inside enclaves.

To profile the performance of SGX enclaves, Intel provides the VTune Amplifier [62]. This tool is designed for profiling applications at the instruction level. While helpful, it lacks performance insights regarding the specific SGX...
performance metrics. SGX-Perf [73] and TEE-Perf [26] overcome this limitation by allowing developers to trace enclave execution and providing SGX performance metrics such as enclave transitions and paging. However, SGX-Perf supports only applications that use the Intel-SGX Software Development Kit. In addition, both SGX-Perf and TEE-Perf do not support runtime monitoring of the performance overhead of an application running inside an enclave. Thus, they cannot support SGX frameworks to tune system parameters during runtime to improve the performance of the applications, for example by increasing the number of threads on the inside or outside of an enclave.

To summarize, TEEs are widely adopted to provide strong security guarantees for applications running in an untrusted environment, e.g., a public cloud. However, there is a lack of tools to monitor the performance of these applications running inside TEE enclaves at runtime. We fill this gap by designing and implementing TEEMon, which allows users to monitor the performance of their applications running in TEEs and to identify performance issues and bottlenecks in real-time. More specifically, TEEMon has the following design features:

1. **Lightweight.** TEEMon incurs low performance overhead while providing useful and accurate performance profiling.

2. **Transparency.** TEEMon does not require modification of the monitored application.

3. **Generality.** TEEMon is framework-agnostic and can be used with many SGX frameworks such as SCONE [25], Graphene-SGX [70], or SGX-LKL [59].

   We implemented TEEMon to monitor the performance of applications running inside Intel SGX enclaves during runtime. In this work, we focus on Intel SGX since it is widely used in practice, although the technique can be applied to other TEEs as well. We evaluated TEEMon using real-world applications and state-of-the-art SGX frameworks. Our evaluation shows that TEEMon has a negligible overhead from 5% to 17% depending on running applications while providing useful performance metrics data for users with an intuitive visualization during runtime. In addition, to the best of our knowledge, this work is the first providing an intensive performance comparison between state-of-the-art Intel SGX frameworks. Lastly, TEEMon has been tested and integrated with Kubernetes to monitor over 6000 distributed SGX enclaves in production, where it was used to track various performance metrics and has allowed the developers of the SCONE framework to continuously monitor the impact of different software generations on a detailed level (e.g., consumption of the enclave page cache, page faults, etc) [23].

### 2 Related Work

There exist only a few tools to profile and monitor applications executed in TEEs at runtime. We briefly report on them, as well as more generic profilers and monitoring tools. Table 1 summarizes our survey.

#### 2.1 Profilers

Over the years, numerous profiling tools and approaches have been proposed. Ball et al. [27] first proposed a set of optimal algorithms for program profiling and instruction tracing to reduce the overhead of profilers. Hardware-specific tools such as LIKWID [63, 69] for x86 environments and MemProf [48] for NUMA systems make use of hardware counters allowing developers to explore optimization opportunities specific to the underlying system architecture. Linux `perf` [34] provides low-level system metrics by attaching to tracepoints, performance counters or probes similarly to eBPF [36]. But it does not offer support for TEEs and it cannot provide profiling data for applications running inside SGX enclaves. VTune Amplifier [62], a commercial analysis tool by Intel, offers in-depth analysis for SGX applications. With the help of special hardware features, it gives detailed information regarding time spent on each method or function call but it provides no support for SGX specific metrics like EPC paging. Further, it depends on the Intel hardware architecture and does not support other vendors. Another similar SGX-specific profiler is SGX-perf [73], which provides statistics on enclave entries and exits as well as EPC paging events based on kprobes [39]. SGX-Perf is limited to applications using the Intel SDK for SGX and does not support monitoring during runtime since it implemented a two-phased record and report approach. TEEMon focuses on continuous monitoring during runtime to provide insights into performance helping to identify the root cause of any bottlenecks and revealing opportunities for performance improvement.

The `gprof` [40] tool can provide developers with an execution profile by counting function invocations as well as

| Tool   | Framework Agnostic | Paging | Enclave Transitions | Orchestrated Applications | Real-Time Reports | Granularity |
|--------|--------------------|--------|---------------------|--------------------------|-------------------|-------------|
| LIKWID | ✓                  | ×      | ×                   | ✓                        | ✓                 | λ, ℓ, ω¹   |
| perf   | ✓                  | ×      | ×                   | ×                        | ×                 | λ, ℓ, ω¹   |
| MemProf | ✓                | ×      | ×                   | ×                        | ×                 | λ, ℓ, ω¹   |
| TEE-Perf | ✓              | ×      | ×                   | ×                        | ×                 | λ, ℓ, ω¹   |
| gprof  | ✓                  | ×      | ×                   | ×                        | ×                 | λ, ℓ, ω¹   |
| VTune  | ✓                  | ×      | ×                   | ×                        | ×                 | λ, ℓ, ω¹   |
| SGX-Perf | ×               | ✓      | ✓                   | ×                        | ×                 | λ, ℓ, ω¹   |
| SGXTOP | ✓                  | ✓      | ✓                   | ×                        | ×                 | λ, ℓ, ω¹   |
| TEEMon | ✓                  | ✓      | ✓                   | ✓                        | ✓                 | λ, ℓ, ω¹   |

Table 1. Profile/monitoring tools for SGX. Granularity can be: λ=function, ℓ=object, ω=event, ω²=system.

¹System-wide statistics are available in LMS [63].
the time spent on each function. However, it is limited to C, Pascal, and Fortran77 programs and does not offer cross-platform support. TEE-perf [26] is an application profiler for trusted execution environments, offering method-level profiling and flame-graph visualizations. Also, it is platform-independent by using software level counters for performance measurements. The performance overhead of TEE-perf is up to 5.7× higher compared to that of Linux perf as the injected code runs on each function call [26]. This, in turn, limits its use to development environments as high overheads are unacceptable in production. All of the aforementioned profilers offer application-specific performance data, but some are platform-dependent, some language-dependent and some are proprietary. Besides, most of the profilers mentioned (i.e., TEE-perf, gprof, SGX-Perf, and VTune Amplifier) are adapted for usage in development and testing stages but are not suitable for providing continuous monitoring due to their high-performance overhead. While developed within a security context, approaches such as SGX-Step [71] could also be used to debug applications in TEEs but typically incur a substantial slowdown. Note that the state-of-the-art monitoring and performance profilers such as TEE-perf [26] report an average slowdown factor of 1.9× compared to native SGX executions. Closely related to TEEMon, SGX-TOP [49] continuously displays SGX-related metrics, which are also collected by the TEE metric exporter (Section 4). However, SGX-TOP focuses solely on displaying SGX-related metrics in a terminal, while lacking archival functionality as well as the combination of multiple metrics into one interface as provided by TEEMon. TEEMon is designed to provide a more holistic monitoring application. In addition, SGX-TOP can be used only with single-node applications, whereas TEEMon supports distributed applications deployed in multiple nodes (e.g., using Kubernetes).

### 2.2 Distributed Monitoring

In a distributed computing environment, applications require constant monitoring to be able to recover and fix deployment issues, fix application-specific bugs or to adjust deployment depending on the current load on the system. Major cloud providers offer proprietary monitoring solutions to their clients, such as Amazon CloudWatch [6], Google Cloud’s Operations [13], or IBM SysDig [19, 30]. These monitoring systems provide hundreds of metrics regarding the cloud infrastructure and applications. However, those are dependent on the cloud provider and are usually billed depending on the number of metrics requested. Besides, in multi-cloud infrastructures, one would need to support and maintain multiple monitoring systems depending on the cloud providers.

As a result, different companies like New Relic [5], SolarWinds [1], Datadog [7], AppDynamics [4], SignalFx [12] and Dynatrace [2] offer managed solutions to monitoring and software analytics for dynamic micro-service architectures. These options provide a solution to the vendor lock-in issue and offer a comprehensive list of services including application and infrastructure analytics. They also support ready-made visualizations and machine learning capabilities running on top of accumulated data for better insights, such as SysDig for SGX capable bare-metal servers at IBM-Cloud [11]. However, none of them were designed to monitor and analyze the performance of applications running inside of TEE enclaves. Our proposed framework additionally supports containerized applications and orchestration management system such as Kubernetes (Section 5.4) thus, can be integrated into TEE-enabled cloud environments [72].

### 3 Background

#### 3.1 Intel Software Guard eXtensions (SGX)

SGX is a set of x86 ISA instructions to secure code and data of applications available since the Intel Skylake\(^2\) architecture [24, 54]. SGX introduces a concept of a secure enclave, i.e., a hardware-protected memory region for code and data protected by the CPU with confidentiality and integrity features. A dedicated region of physical memory called the Enclave Page Cache (EPC) is reserved for enclaves. EPC is protected by an on-chip Memory Encryption Engine (MEE), which transparently encrypts and decrypts the cache lines as they are respectively written to and read from EPC. SGX provides a call-gate mechanism to control entry into, and exit from, the TEE [33]. In most processors, the EPC is limited to ~128 MB, and only ~94 MB can be used for applications [33]. However, the latest generations of Intel Xeon processors are equipped with a larger sized EPC. Currently, Intel SGX has been offered in clouds [38, 45], enabled plenty of confidential cloud-native applications, e.g., analytics systems [50, 51], key management system [41], and secure software update [57].

#### 3.2 SGX Frameworks

To run legacy applications with Intel SGX without any source code modification, SGX frameworks such as SCONe [25], SGX-LKL [59], and Graphene-SGX [70] can be utilized.

**SCONE and SGX-LKL.** SCONe [25] is a shielded execution framework using Intel SGX. To run applications inside SGX enclaves, programs are linked against a modified standard C library, i.e., SCONe 11bc. In this model, the whole application is confined to the enclave memory and the interaction with the untrusted system is executed via a system call interface. SCONe leverages an asynchronous system call mechanism: threads inside of the enclave execute tasks of the application, pushing system calls to the outside of the enclave. Threads outside of the enclave asynchronously execute the system calls and push results back. In addition, SCONe natively integrates with Docker [55] to seamlessly deploy micro-service based applications using container images. A similar approach is implemented by SGX-LKL [59], which

\(^2\)https://software.intel.com/en-us/articles/an-overview-of-the-6th-generation-intel-core-processor-code-named-skylake
also provides a framework that links applications against a modified standard C library (musl-1.1bc).

Graphene-SGX. Graphene-SGX [70] is an open-source SGX implementation of the original Graphene library OS. Similar to Haven [28], it runs a complete library OS inside of SGX enclaves and lets developers run their applications with Intel SGX without any code modifications. Graphene-SGX facilitates protection through a manifest file that contains user defined security policies and a list of trusted libraries (with their cryptographic SHA-256 hashes) required by the application. Thus, the manifest file allows for a fine granular definition of trusted resources.

3.3 BPF and eBPF
The scope of the original BSD Packet Filter (BPF) [53] was limited to network monitoring and packet filtering, by leveraging RISC CPU registers. It efficiently filters network packets without copying packets to user-space before analyzing them. The extended BSD Packet Filter (eBPF) is capable of taking advantage of modern x86 CPU architectures, 64-bit registers, and just-in-time compilation since the Linux kernel 3.15 kernel. Although the original BPF project started as a network monitoring tool, nowadays eBPF programs can be attached to a multitude of hooks in the Linux kernel. eBPF added methods to load custom programs into the eBPF virtual machine for the kernel. In addition, it allows for user space programs to interact with BPF_MMAP data structures in the kernel [15]. BPF_MMAP are generic key/value stores mainly used to share data between kernel and user-space, and between different eBPF programs.

TEEMon uses eBPF to obtain and provide low-level system statistics such as executed system calls or cache misses, as we detail next.

4 Architecture
The main goal of TEEMon is to provide a low-overhead monitoring framework able to offer the performance profiler functionality as previous frameworks [26, 73] while allowing users to continuously keep track of their applications running inside SGX enclaves during runtime, a combination of features that as shown earlier is currently not available (Table 1). In this section, we discuss the architecture of our monitoring framework, explaining the main design decisions.

TEEMon is designed to be generic and applicable to a variety of SGX frameworks without code changes while keeping in mind the state-of-the-art and current best practices in the field of monitoring and observability. Figure 1 shows the high level overview of our monitoring framework.

TEEMon consists of four core components: (i) The performance metrics exporters (PME) collect metrics at different system levels, including the kernel and the TEE environment (e.g. the Intel SGX driver). (ii) The Performance metrics aggregation (PMAG) combines and stores data in a time series database accessed and processed by (iii) the performance metrics analysis (PMAN) component; and (iv) the visualization (PMV) component that presents the monitoring data via a web-service to the user. We provide further details about currently utilized software components in Section 5.

In a nutshell, to capture performance metrics with minimal overhead and without code modification of applications, we design an exporter module for the TEE driver to extract the necessary information for keeping track of applications during runtime. The metrics exporter obtains performance metrics directly from the kernel. Thereafter, the metrics aggregator combines the monitoring metrics from all distributed exporters to provide a global view of the performance of the monitored applications.

TEEMon uses multiple exporters per host machine with individual tasks, e.g., providing SGX-specific or machine-specific metrics. The analysis component examines the aggregated performance metrics to identify the bottlenecks of monitored applications. Lastly, the visualization component continuously presents the performance bottlenecks and critical performance metrics in an intuitive way for users via a web-based interface.

(i) Performance Metrics Exporter (PME).
This component combines two modules: the TEE Metrics Exporter which collects TEE related metrics, and the System Metrics Exporter which collects system metrics. PME exports these collected metrics to the aggregation component in a standardized format. We describe both next.
**TEE Metrics Exporter (TME).** The TME supports two main classes of TEE-related metrics: enclave metrics (initialized enclaves, active enclaves, removed enclaves) and EPC metrics (total EPC pages, free EPC pages, pages marked as old, pages evicted to main memory, pages added to enclaves, pages reclaimed from main memory). Additional metrics could be added through code-adaptation of the utilized TEE driver.

To capture these TEE metrics with low overhead, the TME connects to specific hooks (e.g., sgx_nr_free_pages, sgx_nr_enclaves, or sgx_nr_evicted) in the TEE driver and extracts the data regarding the trusted enclave regions and other specific information to the underlying TEE architecture. There is a single TME instance per machine that requires privileged access to the underlying operating system.

While modifying an existing TEE driver would be feasible [16, 72], developing an additional component provides a modular architecture in order to support current and future TEE technologies, and it avoids excessive and expensive modifications to the underlying TEE subsystem, as this would need additional effort for maintenance. In addition, it can also be used to expose additional metrics regarding the platforms running on top of a TEE. For instance, in Intel SGX, TEEMon can be interchangeably used for SCONE or Graphene-SGX without changing the code of the SGX frameworks.

Our design allows for the PME to be easily customized and used on different TEE platforms as well as for kernel-integrated approaches, such as IBM PEF [18], AMD SEV [44], or Intel TDX [21]. For these virtual machine based security mechanisms, we envision an extension to the hypervisor, e.g. qemu, that integrates the functionality of the TME. The extension would, similar to the TME for SGX, export metrics such as the amount of protective memory requested by each virtual machine. Additionally, other exporters, e.g., the system metrics exporter (SME) described in the next section, can be added to the virtual machine image to export metrics from the guest OS to TEEMon.

**System Metrics Exporter (SME).** The task of the SME (Figure 2) is to collect and export performance metrics from the underlying system infrastructure. To obtain low-level system metrics, one needs to access CPU performance counters, kprobes and tracepoints similarly to Linux’s `perf` [34]. This requires writing and running code in kernel space while ensuring it neither corruptions security nor reduces performance.

To overcome these problems, we use eBPF, the in-kernel virtual machine, allowing kernel instrumentation programs to run in a secure and restricted environment. The eBPF programs connect to specified hooks in the host’s kernel. By attaching small eBPF programs to each kernel hook, we can read and extract low-level system statistics and export them to user space via BPF_MAPs.

The metrics are translated into a standard format understood by the metrics aggregation component (e.g., Prometheus [10]), and published to its metric endpoint (e.g., a web server) to be scraped. The current TEEMon implementation stores metrics as a time-series database, a metrics retrieval component, and an HTTP server. It collects, processes, and aggregates a large number of metrics, from a dynamically changing list of services, with low overhead on the applications. Using its time-series database, it stores all metrics data samples locally and groups them into chunks for faster retrieval. Additionally, it allows for multi-dimensional data with the help of metric labels specified as a set of key-value pairs, e.g., system calls with a timestamp, system-call number, and the number of occurrences.

To support the analysis of performance metrics, PMAG supports data queries over specified time ranges and labeled dimensions. It provides detailed quantitative analysis by selecting and applying aggregation functions to query results. PMAG can connect to every service exposing a metrics endpoint, and users of TEEMon can easily add their application metrics to it. For example, a user can instrument applications to export monitoring metrics in the standard text-based format as specified by the OpenMetrics project [17] and expose them to a REST endpoint. From this endpoint, PMAG can collect the measured metrics.

| Type        | Method               | Field                                      |
|-------------|----------------------|--------------------------------------------|
| Sys. call   | Kernel tracepoints   | `raw_syscalls:sys_enter`                   |
| metrics     |                      | `raw_syscalls:sys_exit`                    |
| Cache       | Kprobes              | `add_to_page_cache_lru`                    |
| metrics     |                      | `mark_page_accessed`                       |
|             |                      | `account_page_dirtied`                     |
|             |                      | `mark_buffer_dirty`                        |
| Context     | Perf. events          | `PERF_COUNT_HW_CACHE_Misses`               |
| switches    |                      | `PERF_COUNT_HW_CACHE_REFERENCES`           |
| Page        | Perf. events          | `PERF_COUNT_HW_PAGE_FAULTS`                |
| faults      | Kernel tracepoints   | `exceptions:page_fault_user`               |
|             |                      | `exceptions:page_fault_kernel`             |

Table 2. System Metrics collected by TEEMon.
new metrics: (i) Push — providing an endpoint where services can push their metrics at the rate they happen or (ii) Pull — the monitoring system pulls the metrics from the metrics endpoints on each service periodically.

The push-based approach allows services to continuously push metrics in real-time and is mainly used by event-based monitoring services like statsd [9]. However, event-based monitoring can lead to congestion and overloading of the entire monitoring systems during sudden events bursts.

The pull-based approach requires the metrics exporter component to provide an endpoint where the monitoring service can subsequently scrape the metrics at specified intervals. Consequently, the resulting data traffic can be managed easier and it lightens the load on the monitoring service itself, compared to having to ingest hundreds of metrics per second as it might happen in the case of system metrics. Additionally, centralizing data ingestion by the system eliminates the issue of misbehaving services pushing garbage data which might turn into a DoS attack on the monitoring system. The downside to the pull approach is the need to know which exporters need to be scraped. This can be solved by using a service discovery system, i.e., a centralized catalog of the running applications and their respective REST endpoints. The monitoring service also acts as a health checker and can alert in case the monitoring target is unreachable. TEEMon relies on a pull approach (from the PMAG component) to collect the monitoring data from the TEE Metrics Exporter and System Metrics Exporter components.

(iii) Performance Metrics Analysis (PMAN).

Although the PMAG component offers data queries and aggregation functions, it lacks support for metrics visualization and analytics. Thus, we design the PMAN component to analyze the aggregated data from the PMAG component in real-time, to identify the bottlenecks or potential anomalies, and to report them to the visualization component for inspection. In addition, the PMAN component has the ability to aid the identification of bottlenecks in applications running inside TEE enclaves. Technically, we make use of threshold-based approaches to detect anomalies in monitoring data. We identified these thresholds using benchmarking with real-world SGX-based applications. PMAN analyzes the time-series monitoring data using slide window computations, e.g., it processes every minute for the last five minutes of the monitoring data. In each time window, PMAN not only compares the monitoring data with user-defined thresholds to detect anomalies but also provides a box plot for SGX metrics. PMAN supports handling anomalies in several ways including alerting, dashboard updating, and logging. Administrators or developers of SGX-based applications can use this information to discover or identify the root of bottlenecks. Note that PMAN can be further extended to perform more advanced analytics, such as the correlation between SGX metrics and configuration parameters of applications, or performance prediction.

(iv) Performance Metrics Visualization (PMV).

Visualizations are crucial for monitoring services, especially when dealing with complex time-series metrics to spot underlying issues or to quickly infer performance trends. Additionally, in cases of failures or incidents, it is useful to limit the view of data to a specific time frame. However, choosing the right type of visual representation is not trivial, as it depends as much on individual preferences as on the metrics that a user is trying to visualize. The PMV component currently supports several visualization options, e.g., graphs, histograms, gauges, gradient fills, tables, etc. It is also possible to group different metrics so that metrics from the same service or serving the same purpose are shown on the same dashboard. We provide a set of intuitive graphs and visual representations of the measured and analyzed metrics, while still allowing users the freedom to modify them or add new metrics according to their needs and preferences.

5 Implementation

The current TEEMon prototype supports the Intel SGX TEE, due to its wide adoption in practice, both in academia and in industry. Our design is however generic and can be extended for other TEEs. We implemented the SGX Exporter for the TEE Metrics Exporter component. We instrumented the Linux SGX driver and developed several eBPF programs to implement the Performance Metrics Exporter component. Figure 1 shows the architecture of TEEMon. We rely on Prometheus [10] (an open-source time-series database) to implement the Performance Metrics Aggregation components, as well as an ad-hoc python program used by the Performance Metrics Analysis (PMAN) to digest raw metrics data and perform threshold analysis. Lastly, we use Grafana [14], a widely used framework, to visualize the collected metrics. We exploit Grafana also for its metric queries, analysis, and various visualization options, thus it’s easy to be integrated with the Performance Metrics Analysis component.

The combination of multiple system-wide sources for various metrics allows TEEMon to provide a broad insight into the monitored system and its executed applications. In comparison to fine grained performance analysis tools, e.g., perf, TEEMon collects key metrics on a system wide level with lower granularity, frequency and only little instrumentation, where perf-like tools may record every event, function call or object change at the application level for advanced analysis features such as call graphs. TEEMon does not completely trace an application during its runtime but only captures system-wide key events, i.e., important performance metrics, such as an enclave creation or the execution of a system call, thus limiting its impact on overall performance. Additionally, monitored metrics are usually only counted, requiring very little processing at runtime. The data retrieval frequency can...
be adjusted, by default, the different exporters are queried for data only every 5 seconds. In the remainder, we describe additional implementation details and the lessons learned during the process.

5.1 Performance Metrics Exporter (PME)

**TEE Metrics Exporter (TME).** In the implementation of the framework, we decided to initially support the Intel SGX platform, as one of the most mature TEE technologies in the market. To collect the SGX metrics, we instrument the official Intel SGX driver source code at specific function calls. Some of the monitored metrics are listed in §4.

All metrics in the SGX driver are instrumented in a similar fashion. The use of module parameters ([64, Chapter 2]) was justified as there is currently no SGX-enabled instrumentation library supporting the C programming language. Doing so, for each metric, there is a file with the same name in /sys/module/isgx/parameters. This is used to write the metric value while the module is loaded and running. Our adaptations to the Intel SGX driver span only 42 lines of code.

While we instrument the SGX driver from Intel, TEEMon only indirectly supports the official Intel SDK for SGX. TEEMon doesn’t monitor OCalls/ECalls specific to the Intel SDK for issuing system calls to the kernel. However, the system calls resulting from OCalls are indeed monitored by TEEMon at the kernel level.

In order to get the SGX metrics into the aggregation component, an interface component is needed. It is implemented in Python and takes advantage of the Flask microframework [8, 42] to expose the metrics via a REST/HTTP endpoint. The SGX Exporter reads the metrics and exposes them in the OpenMetrics [17] format to its metrics endpoint. From this endpoint, the aggregation component can pull the performance metrics during runtime.

**System Metrics Exporter (SME).** The SGX driver metrics themselves are insufficient to show all interactions of a trusted application inside enclaves with the untrusted part of the system. System and infrastructure metrics are additional important cornerstones to monitor applications running inside Intel SGX enclaves.

For instance, the SGX driver only contains the code executed during enclave initialization and functions controlling the EPC pages but it does not interact with other parts of an application’s execution cycle such as entering or exiting the enclave, system calls handling, etc. These system metrics are provided by three smaller components, each exposing a subset of the overall metrics needed:

**eBPF-Exporter.** Our implementation is based on the exporter for custom eBPF metrics by Cloudflare [32]. The exporter contains small eBPF programs written in C to extract metrics during runtime³. Using kernel probes and trace points, these eBPF programs are executed by the kernel whenever specific events are triggered and enable us to, e.g., count and report occurrences of page faults during runtime. Metrics currently collected by the eBPF-Exporter consist of System calls, Context switches, Page Faults, and Cache statistics while custom eBPF programs can be added if necessary.

**Node-Exporter⁴.** The node exporter (written in Go) is part of the Prometheus project and exports machine metrics available through the /proc and /sys directories in Linux environment. We integrated the node exporter into TEEMon and reduced the reported metrics to CPU statistics, Memory statistics, File system statistics, and Network statistics.

**cAdvisor⁵.** To provide utilization metrics for Docker containers, Google created the cAdvisor web-service. We integrated cAdvisor into TEEMon to collect and store per container metrics. Afterwards, these metrics are then continuously visualized in a front-end, e.g., Grafana. The provided metrics can be adjusted depending on the desired level of information and use case [37].

5.2 Performance Metrics Aggregation (PMAG)

Our monitoring system uses Prometheus [10] as the Metrics Aggregation Service that collects all metric data from multiple sources and generates insights by querying and aggregating the data. In particular, we chose Prometheus for its extensibility that allows us to gather internal metrics via a REST/HTTP endpoint.

5.3 Performance Metrics Visualization (PMV)

We make use of Grafana to implement the visualization component of TEEMon. Grafana is an open-source tool for metrics visualization and analysis [14]. We use it to implement TEEMon’s visualization component. It supports various data sources (e.g., Prometheus, InfluxDB, ElasticSearch, etc.) and a broad set of visualization widgets (e.g., graphs, single stats, tables, heat maps, etc.) integrated into the dashboards.

Currently, our prototype consists of three dashboards: (i) an SGX dashboard showing EPC metrics and a selection of metrics provided by eBPF programs, (ii) a Docker dashboard showing performance data provided by cAdvisor from running Docker containers, and (iii) an infrastructure dashboard showing metrics from both Node-Exporter and eBPF-Exporter.

Figure 3 shows a partial screenshot of the SGX dashboard presented by TEEMon. Its frontend allows the user to apply a process filter, e.g., redis-server, for the continuously updated metrics or select a desired time range from historical data. The Figure presents recorded data for the Redis database during a benchmark with its two phases (populating the database and executing queries) visible as two consecutive curves. From the graphs, the user can, for example, study

³https://github.com/iovisor/bcc/

⁴https://github.com/prometheus/node exporter

⁵https://github.com/google/cadvisor
well-established API with a uniform set of resources, as well

TEEMON

components are encapsulated in individual Docker

containers for quick deployment on a single host but they can also be deployed in virtual machines or by an orchestra-

tor, such as Kubernetes, an industry-standard for container

orchestration. It features an application-centric design, a

well-established API with a uniform set of resources, as well

as a powerful ecosystem of third-party tools and extensions. Its controllers allow applications and infrastructures to be

defined in a declarative manner. It supports up to 5000 server-

nodes in a single cluster [20].

Helm⁶, a package manager for Kubernetes applications uti-

lizes charts as application definitions for Kubernetes. These

charts can easily be deployed, managed, and distributed. We

created a chart to install TEE.MON in large-scale infrastruc-

tures managed by Kubernetes.

In Kubernetes, each of TEEMon’s metrics exporters is
deployed (using Helm) in a daemon-like fashion (as Daemon-

Set resource). DaemonSets are deployment configurations

that enforce exactly one application instance (pod) running

per node in the cluster. This deployment configuration in-

cludes dynamically added nodes. Additionally, Kubernetes

offers service discovery and resource annotations that TEE-

Mon uses to connect the performance metric aggregation

component (e.g., Prometheus) to periodically scan for run-

ning metrics exporters. These two features allow TEEMon
to adapt to arbitrary changes in the cluster topology.

The TEEMon chart also allows for more advanced sched-

uling scenarios. For example, in a heterogeneous cluster,
specific Kubernetes labels, i.e., taints, can be used to deploy

applications based on the availability of hardware features.

Thus, TEE-related metrics exporters can be deployed selec-
tively on nodes that support TEEs, e.g., Intel-SGX.

6 Evaluation

This section presents the experimental evaluation of TEE-

Mon using real world applications and various Intel

SGX frameworks. After describing our evaluation settings

(§6.1), we evaluate the overhead of TEEMon in monitoring

application running inside SGX enclaves, for monitoring

overhead (§6.2) and specific application overheads (§6.3).

Additionally, we present findings of continuous code pro-

filing in §6.4. Next, we show the usability of TEEMON in

identifying the cause of performance bottlenecks of state-of-
The-art Intel SGX frameworks including SCONE, SGX-LKL, and Graphene-SGX (§6.5). Our evaluation demonstrates that

the design of TEEMon is generic and it can be transparently

used across a variety of SGX frameworks without changing

their source code.

5.4 Deployment with Kubernetes

TEEMon components are encapsulated in individual Docker

containers for quick deployment on a single host but they can also be deployed in virtual machines or by an orchestra-

tor, such as Kubernetes, an industry-standard for container

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applications based on the availability of hardware features.

Thus, TEE-related metrics exporters can be deployed selec-
tively on nodes that support TEEs, e.g., Intel-SGX.

6.1 Experimental Setup

Testbed. We used two machines connected via a switched

1 GBit Ethernet network (one hop) to conduct experiments

measuring the performance of different Intel SGX frame-

works using TEEMon. The desktop machine is a Fujitsu

ESPRIMO P957/E90+ desktop machine with an Intel® Core

i7–6700 CPU, with 32 GB of RAM, running Ubuntu 16.04.6
(kernel v4.15.0) on an SSD SATA-based disk. The server has

an Intel® Xeon® CPU E3–1280 v6 processor and 64 GB

main memory, running Ubuntu 18.04 (kernel v4.15.0–70)

with the microcode package 3.20191115 installed (microcode

revision 0xca) to mitigate risks against recent SGX-related

attacks [47, 52].

Methodology. For overhead measurements, we report the

average evaluation results of 10 runs and examine several

configurations for each of the evaluated systems:

- Native SGX (without deploying TEEMon), using the

  official Intel SGX driver. We used the native version

  as the evaluation baseline.
- Activating TEEMon with only TEE Performance Met-

  rics Exporter (PME) component (i.e., activating the

  eBPF-Exporter and the SGX Metrics Exporter).
- Activating TEEMon with all components.

Figure 3. Partial screenshot of TEEMon showing SGX-

related metrics.

The enclave page cache (top row) utilization, the occurrences

of page faults (bottom right), or the distribution of system

calls (middle left) during runtime.

⁶https://helm.sh
We evaluate the overhead induced by TEEMon while monitoring three real-world applications. Specifically, we use a document database (i.e., MongoDB (v3.6.3) [3]), a web-server (i.e., NGINX (v1.14.0) [61]), and an in-memory key-value store (i.e., Redis (v5.0.5) [65]). We selected SCONE in this experiment for its ease of use compared to other SGX frameworks. However, we designed and implemented TEEMon in the way that it can also be used with other SGX frameworks such as SGX-LKL, and Graphene-SGX (see §6.5).

We profile these applications in three different configurations: (i) Native SGX (Monitoring OFF), (ii) TEEMon with only the PME component (Monitoring OFF + eBPF ON), and (iii) full TEEMon with all components (Monitoring ON). Figure 5 presents our results. We show the average over 10 executions, normalized against the throughput of the native SGX version, without enabling TEEMon. The applications’ throughput varies from 87% of baseline executions for NGINX to 95% for MongoDB. The eBPF programs running in the kernel contribute for half of the performance drop, and other TEEMon components contribute the other half. This is expected since several eBPF programs are attached to frequently used performance counters (e.g., cache misses, references, system calls, page faults, and context switches).

In some cases (i.e., number of context switches) we instrumented both hardware and software counters with 99 Hz and this accounts for some of the added overhead. This extra overhead can be reduced by disabling unnecessary performance counters, reducing sampling frequency for software counters, or filtering metrics like system calls and context switches to only a specified PID. To facilitate filtering, we provide a macro for some of the programs which can be set in the eBPF configuration file.

### 6.2 Monitoring Overhead

We begin by evaluating the overhead of TEEMon by measuring the CPU and memory footprint of its components, to better understand what is the overhead of each component. We execute this experiment over 24 hours, by deploying TEEMon on the desktop machine to collect the performance metrics in the system and measure the CPU and Memory usage for each module of each component.

Figure 4 (a) shows the CPU utilization of each component in TEEMon. Overall, we observe a modest CPU utilization, and at most 3% on average during the 24 hours for the cAdvisor component. We envision future versions of TEEMon where this component is deactivated to further reduce interferences induced by the tool itself.

Next, Figure 4 (b) shows the average memory consumption of each monitoring component. The aggregation component of TEEMon (on top of Prometheus) is the most memory-eager one. The overall memory footprint of TEEMon is ~700 MB. While all other components use 100 MB on average, Prometheus allocates 4× as much. This is expected by design, the aggregator keeps all currently used data in memory for faster retrieval. Prometheus’ memory usage can be reduced by setting a cache limit (default is 2 GB).

In summary, the overhead of our monitoring framework is negligible for today’s standards, allowing users to deploy it in production environments and continuously analyze monitoring data and performance insights of applications running inside SGX enclaves. As our approach requires no changes to the monitored application and gathers SGX-related statistics at the driver level, no additional memory from the enclave page cache (EPC) is used by TEEMon.

### 6.3 Overhead with Real-world Applications

We evaluate the overhead induced by TEEMon while monitoring three real-world applications. Specifically, we use a document database (i.e., MongoDB (v3.6.3) [3]), a web-server (i.e., NGINX (v1.14.0) [61]), and an in-memory key-value store (i.e., Redis (v5.0.5) [65]). We selected SCONE in this experiment for its ease of use compared to other SGX frameworks. However, we designed and implemented TEEMon in the way that it can also be used with other SGX frameworks such as SGX-LKL, and Graphene-SGX (see §6.5).

We profile these applications in three different configurations: (i) Native SGX (Monitoring OFF), (ii) TEEMon with only the PME component (Monitoring OFF + eBPF ON), and (iii) full TEEMon with all components (Monitoring ON). Figure 5 presents our results. We show the average over 10 executions, normalized against the throughput of the native SGX version, without enabling TEEMon. The applications’ throughput varies from 87% of baseline executions for NGINX to 95% for MongoDB. The eBPF programs running in the kernel contribute for half of the performance drop, and other TEEMon components contribute the other half. This is expected since several eBPF programs are attached to frequently used performance counters (e.g., cache misses, references, system calls, page faults, and context switches).

In some cases (i.e., number of context switches) we instrumented both hardware and software counters with 99 Hz and this accounts for some of the added overhead. This extra overhead can be reduced by disabling unnecessary performance counters, reducing sampling frequency for software counters, or filtering metrics like system calls and context switches to only a specified PID. To facilitate filtering, we provide a macro for some of the programs which can be set in the eBPF configuration file.
We conclude our experimental evaluation by showing that while tracking statistics about system calls, page faults, and clock_gettime, As a result, the number of
TEEMON
8
6.5 Head-to-Head of SGX Framework

Commit ff8a1a3d, master branch.

Commit fab5a2b7c, master branch.

Commit e9bae31, master branch.

https://github.com/RedisLabs/memtier_benchmark

Figure 7. Changes in throughput for Redis at different stages of code evolution and native Redis.

6.4 Continuous Profiling during code evolution

Besides using it for monitoring deployed applications at a large scale for overall system health and performance, TEE-Mon can be easily used to track the impact of code changes. Our approach to continuous integration includes compilation and benchmarks of several applications including Redis while tracking statistics about system calls, page faults, and EPC pages, provided by TEE-Mon.

As a showcase, we evaluate two minor releases of SCONE and run the Redis-benchmark application using TEE-Mon to monitor its execution. This allowed us to find that the futex and clock_gettime system calls dominated over the read/write system calls to receive and send data. Thus, it indicated a performance bottleneck as all system calls trigger an expensive enclave exit.

Figure 6 shows the occurrences of selected system calls for two consecutive code commits, as monitored by TEE-Mon during the execution of Redis compiled with SCONE. Commit 572bd1a5 precedes commit 09fe9a1. For the specific commit 572bd1a5 we found that the clock_gettime system calls peaked at over 270,000/sec while read and write system calls were at a tenth of that.

As depicted in Figure 7, the specific code changes yielded in an almost doubling of average throughput. The graph shows the performance measurements of Redis using Redis-benchmark on a single host.

With commit 09fe9a1 the handling of the clock_gettime system call was improved towards handling it on the inside of the enclave without triggering a system call in the kernel. As a result, the number of clock_gettime system calls to the kernel and enclave exits is dramatically reduced allowing Redis to handle more requests per second. With this optimization, we measured at most 100 clock_gettime system calls per second while the maximum read and write system calls increased from 23 to 32 per second.

For commit 572bd1a5, Redis achieves a throughput of 267,952.22 IOP/s. With the commit 09fe9a1, the throughput of Redis increased to 621,504 IOP/s.

6.5 Head-to-Head of SGX Framework

We conclude our experimental evaluation by showing that TEE-Mon is designed in a generic way so that it can be used for different Intel SGX frameworks without changing their source code. We focus on a head-to-head comparison using the Redis in-memory key-value store as application, deployed and run inside Intel SGX enclaves using several SGX frameworks. In addition, we also demonstrate that based on the performance metrics and statistics provided by TEE-Mon, we can identify the cause of bottlenecks of these SGX frameworks.

We benchmarked Redis (v5.0.5) running inside SGX enclaves using SGX-LKL, SCONE, and Graphene-SGX. These SGX frameworks can run legacy applications Intel SGX without changing their code, simply by recompiling or relinking Redis using their provided compilation toolchains.

While Redis was executed directly on the host, we adapted the configuration of Redis to allow for stable execution with all frameworks. Foremost, we disabled the periodic creation of persistent snapshots, it requires the availability of the fork() system call within the SGX-enclave, which is not available in SGX-LKL and Graphene-SGX. Furthermore, we configured Redis to use at most 1 GB of memory, i.e., the heap size of the enclave configured for all SGX frameworks.

We make use of the menttier_benchmark suite to measure the performance of Redis and configure it to use 8 concurrent threads for optimal performance. Hence, the indicated number of connections is always a factor of 8.

First, we pre-populate the database with 720,000 keys. During the measurements, the benchmark issues GET requests. The menttier_benchmark is configured to use a pipeline of 8 requests and 8 connections per client-thread as these settings provided the best results in preliminary tests. We run experiments with different Redis database sizes (78 MB, 105 MB, and 127 MB) by setting the size of values (in the key-value messages) of 32, 64, and 96 bytes, respectively. The reason we conducted the experiments with different database sizes is that the most current SGX hardware supports only ~94 MB EPC size (see §3) for applications running inside enclaves. When more memory is required, the applications inside enclaves need to perform the paging mechanism, usually very expensive performance-wise.

Next, we first present the performance comparison of Redis running with different SGX frameworks. Then, we describe how to use performance metrics captured by TEE-Mon to identify the bottlenecks of these SGX frameworks.

#1: Performance Comparison

In the following, we discuss the performance measurements for Redis running with Intel SGX using SGX-LKL, SCONE, and Graphene-SGX. Note that the native version in this experiment is the vanilla Redis running without Intel SGX.

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8https://redis.io/topics/benchmarks

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Figure 8. The throughput comparison between native Redis and Redis with different SGX frameworks. The total memory usage of Redis is set to different sizes of 78 MB, 105 MB, and 127 MB.

Figure 9. The latency comparison between native Redis and Redis with different SGX frameworks. The total memory usage of Redis is set to different sizes of 78 MB, 105 MB, and 127 MB.

Figure 10. The throughput and latency comparison between native Redis and Redis with different SGX-frameworks. The total memory usage of Redis is set to 78 MB.

**Throughput.** Figure 8 shows the throughput of Redis using the different SGX frameworks. The native Redis achieves the throughput of 1.01 M - 1.2 M input/output operations per second (IOP/s) with different Redis database sizes at 320 client connections (Figure 8 (a)). The throughput of native Redis decreases when the number of connections is higher than 320. This is because, above 320 client connections, the host’s network is squeezed at its capacity of 1 GBps (see §6.1).

Meanwhile, Figure 8 (b) depicts a similar behavior of throughput of Redis running with SCONE. The maximum throughput of SCONE is 278 KIOP/s at 560 connections (~23% throughput of native Redis). The throughput of Redis with SCONE drops when the database size increases due to the EPC limitation of the SGX hardware. Increasing the database size from 87 MB to 105 MB reduces the peak performance of Redis with SCONE by 32 KIOP/s (decrease of 12%). Further increasing the database size to 127 MB decreases the peak performance at 29 KIOP/s.

Figure 8 (c) shows the results for the throughput of Redis with the SGX-LKL framework. While Redis with SGX-LKL peaks at 320 connections with 121 KIOP/s (~10% of native Redis throughput), our results also show a steep drop in performance of Redis with SGX-LKL at 560 connections with a steady increase afterward.

Figure 8 (d) shows that, differently from the other SGX frameworks, Graphene-SGX performs best for one client (8 connections) and exhibits a reduced performance for more connections. The peak performance of Graphene-SGX was measured at 20 KIOP/s for 8 connections, (~1.6% of native Redis throughput). Similar to SCONE, Figure 8 (d) shows a drop in throughput of Graphene-SGX if the database size increases from 78 MB to 105 MB. For a single client, the throughput decreases from 20 KIOP/s to 12 KIOP/s.

**Latency.** Figure 9 presents the Redis latency comparison between the different SGX frameworks. As expected, the latency of all evaluated systems increases when the number of connections increases. At 320 connections, the latency of the native Redis is ~2 milliseconds (ms), whereas the latency of Redis with SCONE, SGX-LKL, and Graphene-SGX are ~9 ms, ~20 ms, and ~249 ms, respectively. All latency measurements show an overall similar correlation between the number of connections and the latency. However, Redis with Graphene-SGX imposes a significantly higher latency compared to other frameworks.

Figure 10 (a) and (b) show a performance comparison of native Redis and Redis with different SGX frameworks, with a database size of 78 MB and an increasing number of clients connections. In general, these results only show the overall performance trends of the SGX frameworks. To understand
Page Faults. Figure 11 (a) and Figure 11 (b) show the page faults in user space for Redis and the total page faults per host during the benchmark, respectively. The user space page faults include: no_page_found, write_prot_fault, write_fault and instr_fetch_fault.

While Figure 11 (a) indicates an overall low rate of user space page faults, it also shows that native Redis causes no page faults in user space. For the SGX frameworks, the rate of user space page faults increases with database sizes exceeding the EPC size (~94 MB). This happens when the SGX-enabled Redis reads data that was previously swapped out of the EPC and is unavailable for the current request. For 320 and 580 connections, with the database size of 105 MB, Redis with SCONE reaches the peaks of 0.069 and 0.064 user space page faults. Graphene-SGX and SGX-LKL show a similar pattern of page faults with ~0.03 page faults per 100 requests for larger database sizes. While SCONE and SGX-LKL introduce negligible page faults (e.g., almost no page fault) with the database size of 78 MB which fits into EPC, the measurements show that Graphene-SGX still has the number of page faults of 0.02 per 100 requests.

In contrast to the low rate of user level page faults, Figure 11 (b) shows that on host-wide scope more page faults are registered. Native Redis has 607 total page faults per 100 GET requests for 8 connections, however, this number decreases (<170 page faults) for larger numbers of connections. This closely follows the finding that few connections lead to context switches in native Redis. While SCONE and SGX-LKL have the page fault rates increasing from 500 to 2200 total page faults per 100 GET requests, Graphene-SGX has a significant number of total page faults. For 580 connections and database size of 105 MB, Graphene-SGX has 8996 total page faults per 100 requests on average.

Last Level Cache Misses. Figure 11 (c) illustrates the last level cache (LLC) misses during the benchmark. Compared to native Redis, all SGX frameworks induce an elevated rate of LLC misses. With native Redis we observe 1.8 – 23 LLC misses per 100 GET requests. Instead, SCONE and SGX-LKL achieve similar (yet higher) rates, i.e., 29 to 103 LLC misses per 100 GET requests. Graphene-SGX has the highest LLC misses: 91 for 8 connections and 78 MB database size, and up to 161 LLC misses for 580 connections with 105 MB database size (per 100 GET requests).

Evicted EPC Pages. Figure 11 (d) shows the measured evicted pages from the enclave page cache (EPC). Graphene-SGX has at most 0.02 evicted pages per 100 GET requests for the database size of 78 MB which fits in the EPC. For the database size of 105 MB, Graphene-SGX exhibits at most 0.03
evicted pages per 100 GET requests. SGX-LKL shows a very similar behavior with up to 1.6 evicted pages (per 100 GET requests) for the database size of 78 MB and up to 1.7 evicted pages with the database size of 105 MB. Meanwhile, SCONE has a stark increase of evicted pages compared to other SGX frameworks. With the number of connections of 580 and for the database size of 105 MB, SCONE has 137 evicted pages per 100 GET requests. We attribute the differences to the individual implementation and potential shortcomings of the framework’s enclave memory management.

**Context Switches.** A common cause of SGX performance overheads is costly enclave transitions. The context switches were filtered by PID, to make it easier to monitor specific applications in the system.

Figure 11 (e) shows these results and indicates that per 100 GET requests, Redis with SGX-LKL hits the most context switches. Instead, native Redis exhibits 0.14 context switches per 100 requests for the evaluation with just 8 connections. Since Redis uses an event queue and in combination with the findings shown in Figure 8 (a), we conclude that, for 8 connections, Redis often waits (sleeps) for new messages and thereby causes context switches. With the exception of Graphene-SGX, SCONE and SGX-LKL show a similar pattern for 8 connections.

Figure 11 (f) shows the number of total context switches on the host while the GET requests are issued. The figure suggests the total (host-wide) context switches of Redis with Graphene-SGX increases dramatically (up to 12×) compared to Redis with other SGX frameworks and native Redis. For 580 connections with a database size of 105 MB, Redis with Graphene-SGX has 304 context switches per 100 GET requests, while native Redis has only 37. SCONE and SGX-LKL expose a similar pattern as native Redis, with at most 125 context switches per 100 GET requests. We believe that Graphene-SGX has the lower performance as shown in Figure 10 because it has significantly more context switches than the other frameworks as reported by TEEMon.

Note that Figure 11 (e) shows only the context switches by Redis process itself, including its threads while Figure 11 (f) shows the total (host-wide) amount of context switches which includes the context switches between kernel processes as well as context switches to the ksgxswapd (Intel® SGX swapping daemon) process.

In summary, in this experiment, we show that TEEMon provides detailed performance data during runtime (e.g., cache misses, context switches, page faults, evicted EPC pages, etc) of applications (e.g., Redis) running inside Intel SGX which helps us to understand the performance behavior of the applications. The presented performance metrics by TEEMon are helpful for developers using SGX frameworks to identify performance issues and to provide guidance for improving the performance of these frameworks, especially with regard to scarce resources such as EPC memory and the expensive enclave exit and enter operations (due to system calls). This is achieved by presenting valuable graphs that show, e.g., high occurrences of the clock_gettime system call dominating the desired read-write system calls for network IO. While different metrics could in principal be gathered individually with different tools, TEEMon provides a single frontend for continuous and effortless monitoring of application to analyse their behavior in a production ready environment.

7 Conclusion and Future Work

This paper described TEEMon, a real-time performance monitoring framework for applications running inside TEE enclaves. TEEMon is independent from specific secure execution platforms and applications running on top of it while offering a wide range of performance metrics. Furthermore, it natively supports a micro-service architecture for applications since all components of TEEMon can be deployed using Docker containers. We evaluated TEEMon using real-world applications and state-of-the-art SGX frameworks.

Our evaluation shows that TEEMon incurs a very low overhead, which is only from 5% to 17% depending on running applications, while it provides valuable insights on the measured performance. TEEMon additionally offers a visualization dashboard to inspect in real-time the behavior of the systems being monitored. The evaluation also shows that TEEMon can be used for many different Intel SGX frameworks without changing the framework’s code. The performance metrics provided by TEEMon allow users to pinpoint bottlenecks and performance issues of applications running inside enclaves using different SGX frameworks and identify the source causing the bottlenecks of these SGX frameworks including SCONE, SGX-LKL and Graphene-SGX. Finally, TEEMon has been integrated with Kubernetes to monitor TEE applications running in distributed cluster.

In the future, we will extend and improve TEEMon to offer additional information as well as flexibility to the user. The probes that TEEMon uses to gather kernel data are currently fixed but in the future, on-demand loading should be possible. TEEMon will be made available to the research community.

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