Robust and Efficient Elimination of Cache and Timing Side Channels

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Abstract—Timing and cache side channels provide powerful attacks against many sensitive operations including cryptographic implementations. Existing defenses cannot protect against all classes of such attacks without incurring prohibitive performance overhead. A popular strategy for defending against all classes of these attacks is to modify the implementation so that the timing and cache access patterns of every hardware instruction is independent of the secret inputs. However, this solution is architecture-specific, brittle, and difficult to get right. In this paper, we propose and evaluate a robust low-overhead technique for mitigating timing and cache channels. Our solution requires only minimal source code changes and works across multiple languages/platforms. We report the experimental results of applying our solution to protect several C, C++, and Java programs. Our results demonstrate that our solution successfully eliminates the timing and cache side-channel leaks while incurring significantly lower performance overhead than existing approaches.

I. INTRODUCTION

Defending against cache and timing side channel attacks is known to be a hard and important problem. Timing and cache attacks can be used to extract cryptographic secrets from running systems \cite{4,5,23,29,35,36,40}, spy on Web user activity \cite{12}, and even undo the privacy of differential privacy systems \cite{5,24}. Attacks exploiting timing side channels have been demonstrated for both remote and local adversaries. A remote attacker is separated from its target by a network \cite{14,15,23,26} while a local attacker can execute unprivileged spyware on the target machine \cite{7,9,11,36,45,47}.

Most existing defenses against cache and timing attacks only protect against a subset of attacks and incur significant performance overheads. For example, one way to defend against remote timing attacks is to make sure that the timing of any externally observable events are independent of any data that should be kept secret. Several different strategies have been proposed to achieve this, including application-specific changes \cite{10,27,30}, static transformation \cite{17,20}, and dynamic padding \cite{6,13,24,31,47}. However, none of these strategies defend against local timing attacks where the attacker spies on the target application by measuring the target’s impact on the local cache and other resources. Similarly, the strategies for defending against local cache attacks like static partitioning of resources \cite{28,37,43,44}, flushing state \cite{59}, obfuscating cache access patterns \cite{9,10,13,35,40}, and moderating access to fine-grained timers \cite{33,34,42}, also incur significant performance penalties while still leaving the target potentially vulnerable to timing attacks. We survey these methods in related work (Section VIII).

A popular approach for defending against both local and remote timing attacks is to ensure that the low-level instruction sequence does not contain instructions whose performance depends on secret information. This can be enforced by manually re-writing the code, as was done in OpenSSL\textsuperscript{1} or by changing the compiler to ensure that the generated code has this property \cite{20}.

Unfortunately, this popular strategy can fail to ensure security for several reasons. First, the timing properties of instructions may differ in subtle ways from one architecture to another (or even from one processor model to another) resulting in an instruction sequence that is unsafe for some architectures/processor models. Second, this strategy does not work for languages like Java where the Java Virtual Machine (JVM) optimizes the bytecode at runtime and may inadvertently introduce secret-dependent timing variations. Third, manually ensuring that a certain code transformation prevents timing attacks can be extremely difficult and tedious, as was the case when updating OpenSSL to prevent the Lucky-thirteen timing attack \cite{42}.

Our contribution. We propose the first low-overhead, application-independent, and cross-language defense that can protect against both local and remote timing attacks with minimal application code changes. We show that our defense is language-independent by applying the strategy to protect applications written in Java and C/C++. Our defense requires relatively simple modifications to the underlying OS and can run on off-the-shelf hardware.

We implement our approach in Linux and show that the execution times of protected functions are independent of secret data. We also demonstrate that the performance overhead of our defense is low. For example, the performance overhead to protect the entire state machine running inside a SSL/TLS server against all known timing- and cache-based side channel attacks is less than 5% in connection latency.

We summarize the key insights behind our solution (described in detail in Section IV) below.

• We leverage programmer code annotations to identify and protect sensitive code that operates on secret data. Our defense mechanism only protects the sensitive functions. This lets us minimize the performance impact of our scheme by leaving the performance of non-sensitive functions unchanged.

\textsuperscript{1}In the case of RSA private key operations, OpenSSL uses an additional defense called blinding.
• We further minimize the performance overhead by separating and accurately accounting for secret-dependent and secret-independent timing variations. Secret-independent timing variations (e.g., the ones caused by interrupts, the OS scheduler, or non-secret execution flow) do not leak any sensitive information to the attacker and thus are treated differently than secret-dependent variations by our scheme.
• We demonstrate that existing OS services like schedulers and hardware features like memory hierarchies can be leveraged to create a lightweight isolation mechanism that can protect a sensitive function’s execution from other local untrusted processes and minimize timing variations during the function’s execution.
• We show that naive implementations of delay loops in most existing hardware leak timing information due to the underlying delay primitive’s (e.g., NOP instruction) limited accuracy. We create and evaluate a new scheme for implementing delay loops that prevents such leakage while still using existing coarse-grained delay primitives.
• We design and evaluate a lazy state cleansing mechanism that clears the sensitive state left in shared hardware resources (e.g., branch predictors, caches, etc.) before handing them over to an untrusted process. We find that lazy state cleansing incurs significantly less overhead than performing state cleaning as soon as a sensitive function finishes execution.

II. KNOWN TIMING ATTACKS

Before describing our proposed defense we briefly survey different types of timing attackers. In the previous section, we discussed the difference between a local and a remote timing attacker: a local timing attacker, in addition to monitoring the total computation time, can spy on the target application by monitoring the state of shared hardware resources such as the local cache.

Concurrent vs. non-concurrent attacks. In a concurrent attack, the attacker can probe shared resources while the target application is operating. For example, the attacker can measure timing information or inspect the state of the shared resources at intermediate steps of a sensitive operation. The attacker’s process can control the concurrent access by adjusting its scheduling parameters and its core affinity in the case of symmetric multiprocessing (SMP).

A non-concurrent attack is one in which the attacker only gets to observe the timing information or shared hardware state at the beginning and the end of the sensitive computation. For example, a non-concurrent attacker can extract secret information using only the aggregate time it takes the target application to process a request.

Local attacks. Concurrent local attacks are the most prevalent class of timing attacks in the research literature. Such attacks are known to be able to extract the secret/private key against a wide-range of ciphers including RSA [36], AES [23, 35, 40, 46], and ElGamal [49]. These attacks exploit information leakage through a wide range of shared hardware resources: L1 or L2 data cache [23, 35, 36, 40], L3 cache [26, 46], instruction cache [11, 49], branch predictor cache [2, 3], and floating-point multiplier [4].

There are several known local non-concurrent attacks as well. Osvik et al. [35], Tromer et al. [40], and Bonneau and Mironov [11] present two types of local, non-concurrent attacks against AES implementations. In the first, prime and probe, the attacker “primes” the cache, triggers an AES encryption, and “probes” the cache to learn information about the AES private key. The spy process primes the cache by loading its own memory content into the cache and probes the cache by measuring the time to reload the memory content after the AES encryption has completed. This attack involves the attacker’s spy process measuring its own timing information to indirectly extract information from the victim application. Alternatively, in the evict and time strategy, the attacker measures the time taken to perform the victim operation, evicts certain chosen cache lines, triggers the victim operation, and compares the time to reload the memory content after the AES encryption has completed.

Remote attacks. All existing remote attacks [14, 15, 29, 36] are non-concurrent, however this is not fundamental. A hypothetical remote, yet concurrent, attack would be one in which the remote attacker submits requests to the victim application at the same time that another non-adversarial client sends some requests containing sensitive information to the victim application. The attacker may then be able to measure timing information at intermediate steps of the non-adversarial client’s communication with the victim application and infer the sensitive content.

III. THREAT MODEL

We allow the attacker to be local or remote and to execute concurrently or non-concurrent with the target application. We assume that the attacker can only run spy processes as a different non-privileged user (i.e., no super-user privileges) than the owner of the target application. We also assume that the spy process cannot bypass the standard user-based isolation provided by the operating system. We believe that these are very realistic assumptions because if either one of these assumptions fail, the spy process can steal the user’s sensitive information without resorting to side channel attacks in most existing operating systems.

In our model, the operating system and the underlying hardware are trusted. Similarly, we expect that the attacker does not have physical access to the hardware and cannot monitor side channels such as electromagnetic radiations, power use, or acoustic emanations. We are only concerned with timing and cache side channels since they are the easiest side channels to exploit without physical access to the victim machine.

IV. OUR SOLUTION

In our solution, developers annotate the functions performing sensitive computation(s) that they would like to protect. For the rest of the paper, we refer to such functions as protected functions. Our solution instruments the protected functions such that our stub code is invoked before and after execution of each protected function. The stub code ensures
that the protected functions, all other functions that may be invoked as part of their execution, and all the secrets that they operate on are safe from both local and remote timing attacks. Thus, our solution automatically prevents leakage of sensitive information by all functions (protected or unprotected) invoked during a protected function’s execution.

Our solution ensures the following properties for each protected function:

- We ensure that the execution time of a protected function as observed by either a remote or a local attacker is independent of any secret data the function operates on. This prevents an attacker from learning any sensitive information by observing the execution time of a protected function.
- We clean any state left in the shared hardware resources (e.g., caches) by a protected function before handing the resources over to an untrusted process. As described earlier in our threat model (Section III), we treat any process as untrusted unless it belongs to the same user who is performing the protected computation. We cleanse shared state only when necessary in a lazy manner to minimize the performance overhead.
- We prevent other concurrent untrusted processes from accessing any intermediate state left in the shared hardware resources during the protected function’s execution. We achieve this by efficiently dynamic partitioning the shared resources while incurring minimal performance overhead.

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**Figure 1:** Overview of our solution

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We prevent other concurrent untrusted processes from accessing any intermediate state left in the shared hardware resources during the protected function’s execution. We apply time padding at the end of every protected function’s execution. This ensures minimal overhead while preventing a local attacker from learning the running time of protected functions. Prior schemes applied a large time pad before sending a service’s output over the network. Such schemes are not secure against local attackers who can use local resources, such as cache behavior, to infer the execution time of individual protected functions.

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**Time padding.** We use time padding to make sure that a protected function’s execution time does not depend on the secret data. The basic idea behind time padding is simple—pad the protected function’s execution time to its worst-case runtime over all possible inputs. The idea of padding execution time to an upper limit to prevent timing channels itself is not new and has been explored in several prior projects \cite{6, 18, 24, 31, 47}. However, all these solutions suffer from two major problems which prevent them from being adopted in real-world setting: i) they incur prohibitive performance overhead (90—400\% in macro-benchmarks \cite{47}) because they have to add a large amount of time padding in order to prevent any timing information leakage to a remote attacker, and ii) they do not protect against local adversaries who can infer the actual unpadded execution time through side channels beyond network events (e.g., by monitoring the cache access patterns at periodic intervals).

We solve both of these problems in this paper. One of our main contributions is a new low-overhead time padding scheme that can prevent timing information leakage of a protected function to both local and remote attackers. We minimize the required time padding without compromising security by adapting the worst-case time estimates using the following three principles:

1) We adapt the worst-case execution estimates to the target hardware and the protected function. We do so by providing an offline profiling tool to automatically estimate worst-case runtime of a particular protected function running on a particular target hardware platform. Prior schemes estimate the worst-case execution times for complete services (i.e., web servers) across all possible hardware configurations. This results in an over-estimate of the time pad that hurts performance.

2) We protect against local (and remote) attackers by ensuring that an untrusted process cannot intervene during a protected function’s execution. We apply time padding at the end of every protected function’s execution. This ensures minimal overhead while preventing a local attacker from learning the running time of protected functions. Prior schemes applied a large time pad before sending a service’s output over the network. Such schemes are not secure against local attackers who can use local resources, such as cache behavior, to infer the execution time of individual protected functions.

3) Timing variations result from many factors. Some are secret-dependent and must be prevented, while others are secret independent and cause no harm. For example, timing variations due to the OS scheduler and interrupt handlers are generally harmless. We accurately measure and account for secret-dependent variations and ignore the secret-independent variations. This lets us compute an optimal time pad needed to protect secret data. None of the existing time padding schemes distinguish between the secret-dependent and secret-independent variations. This results in unnecessarily large time pads, even when secret-dependent timing variations are small.

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**Preventing leaks via shared resources.** We prevent information leakage through shared resources without adding significant performance overhead to the process executing the protected function or to other (potentially malicious) processes. Our approach is as follows:
• We leverage the multi-core processor architecture found in most modern processors to minimize the amount of shared resources during a protected function’s execution without hurting performance. We dynamically reserve exclusive access to a physical core (including all per-core caches such as L1 and L2) while it is executing a protected function. This ensures that a local attacker does not have concurrent access to any per-core resources while a protected function is accessing them.

• For L3 caches shared across multiple cores, we use page coloring to ensure that cache accesses during a protected function’s execution are restricted within a reserved portion of the L3 cache. We further ensure that this reserved portion is not shared with other users’ processes. This prevents the attacker from learning any information about protected functions through the L3 cache.

• We lazily cleanse the state left in both per-core resources (e.g., L1/L2 caches, branch predictors) and resources shared across cores (e.g., L3 cache) only before handing them over to untrusted processes. This minimizes the overhead caused by the state cleansing operation.

A. Time padding

We design a safe time padding scheme that defends against both local and remote attackers inferring sensitive information from observed timing behavior of a protected function. Our design consists of two main components: estimating the padding threshold and applying the padding safely without leaking any information. We describe these components in detail next.

**Determining the padding value.** Our time padding only accounts for secret-dependent time variations. We discard variations due to interrupts or OS scheduler preemptions. To do so we rely Linux’s ability to keep track of the number of external preemptions. We adapt the total padding time based on the amount of time that a protected function is preempted by the OS.

• Let $T_{\text{max}}$ be the worst-case execution time of a protected function when no external preemptions occur.

• Let $T_{\text{ext preemt}}$ be the worst-case time spent during preemptions given the set of $n$ preemptions that occur during the execution of the protected function.

Our padding mechanism pads the execution of each protected function to $T_{\text{padded}}$ cycles, where

$$T_{\text{padded}} = T_{\text{ext preemt}} + T_{\text{max}}.$$  

This leaks the amount of preemption time to the attacker, but nothing else. Since this is independent of the secret, the attacker learns nothing useful.

**Estimating $T_{\text{max}}$.** Our time padding scheme requires a tight estimate of the worst-case execution time (WCET) of every protected function. There are several prior projects that try to estimate WCET through different static analysis techniques [19, 25]. However, these techniques require precise and accurate models of the target hardware (e.g., cache, branch target buffers, etc.) which are often very hard to get in practice. In our implementation we use a simple dynamic profiling method to estimate WCET described below. Our time padding scheme is not tied to any particular WCET estimation method and can work with other estimation tools.

We estimate the WCET, $T_{\text{max}}$, through dynamic offline profiling of the protected function. Since this value is hardware-specific, we perform the profiling on the actual hardware that will run protected functions. To gather profiling information, we run an application that invokes protected functions with an input generating script provided by the application developer/system administrator. To reduce the possibility of overtimes occurring due to uncommon inputs, it is important that the script generate both common and uncommon inputs. We instrument the protected functions in the application so that the worst-case performance behavior is stored in a profile file. We compute the padding parameters based on the profiling results.

To be conservative, we obtain all profiling measurements for the protected functions under high load conditions (i.e., in parallel with other application that produces significant loads on both memory and CPU). We compute $T_{\text{max}}$ from these measurements such that it is the worst-case timing bound when at most a $\kappa$ fraction of all profiling readings are excluded. $\kappa$ is a security parameter which provides a tradeoff between security and performance. Higher values of $\kappa$ reduce $T_{\text{max}}$ but increase the chance of overtimes. For our prototype implementation we set $\kappa$ to $10^{-5}$.

**Safely applying padding.** Once the padding amount has been determined using the techniques described earlier, waiting for the target amount might seem easy at first glance. However, there are two major issues that make application of padding complicated in practice as described below.

**Handling limited accuracy of padding loops.** As our solution depends on fine-grained padding, a naive padding scheme may leak information due to limited accuracy of any padding loops. Figure 2 shows that a naive padding scheme that repeatedly measures the elapsed time in a tight loop until the target time is reached leaks timing information. This is because the loop can only break when the condition is evaluated, and hence if one iteration of the loop takes $u$ cycles then the padding loop leaks timing information mod $u$. Note that earlier timing padding schemes do not get affected by this problem as their padding amounts are significantly larger than ours.

Our solution guarantees that the distribution of running times of a protected function for some set of private inputs is indistinguishable from the same distribution produced when a different set of private inputs to the function are used. We
call this property the safe padding property. We overcome the limitations of the simple wait loop by performing a timing randomization step before entering the simple wait loop. During this step, we perform $m$ rounds of a randomized waiting operation. This goal of this step is to ensure that the amount of time spent in the protected function before the beginning of the simple wait loop, when taken modulo $u$, the stable period of the simple timing loop (i.e., disregarding the first few iterations), is close to uniform. This technique can be viewed as performing a random walk on the integers modulo $u$ where the runtime distribution of the waiting operation is the support of the walk and $m$ is the number of steps walked. Prior work by Chung et al. [16] has explored the sufficient conditions for the number of steps in a walk and its support that produce a distribution that is exponentially close to uniform.

For the purposes of this paper, we perform timing randomization using a randomized operation with $256$ possible inputs that runs for $X + c$ cycles on input $X$ where $c$ is a constant. We describe the details of this operation in Section V. We then choose $m$ to defeat our empirical statistical tests under pathological conditions that are very favorable to an attacker as shown in Section VI.

For our scheme’s guarantees to hold, the randomness used inside the randomized waiting operation must be generated using a cryptographically secure generator. Otherwise, if an attacker can predict the added random noise, she can subtract it from the observed padded time and hence derive the original timing signal, modulo $u$.

A padding scheme that pads to the target time $T_{padded}$ using a simple padding loop and performs the randomization step after the execution of the protected function will not leak any information about the duration of the protected function, as long as the following conditions hold: (i) no preemptions occur; (ii) the randomization step successfully yields a distribution of runtimes that is uniform modulo $u$; (iii) The simple padding loop executes for enough iterations so that it reaches its stable period. The security of this scheme under these assumptions can be proved as follows.

Let us assume that the last iteration of the simple wait loop take $u$ cycles. Assuming the simple wait loop has iterated enough times to reach its stable period, we can safely assume that $u$ does not depend on when the simple wait loop started running. Now, due to the randomization step, we assume that the amount of time spent up to the start of the last iteration of the simple wait loop, taken modulo $u$, is uniformly distributed. Hence, the loop will break at a time that is between the target time and the target time plus $u - 1$. Because the last iteration began when the elapsed execution time was uniformly distributed modulo $u$, these $u$ different cases will occur with equal probability. Hence, regardless of what is done within the protected function, the padded duration of the function will follow a uniform distribution of $u$ different values after the target time. Therefore, the attacker will not learn anything from observing the padded time of the function.

To reduce the worst-case performance cost of the randomization step, we generate the required randomness at the start of the protected function, before measuring the start time of the protected function. This means that any variability in the runtime of the randomness generator does not increase $T_{padded}$.

```plaintext
// At the return point of a protected function:
// $T_{begin}$ holds the time at function start
// $I_{begin}$ holds the preemption count at function start
for $j = 1$ to $m$
    Short-Random-Delay()
    $T_{target} = T_{begin} + T_{max}$
    $overtime = 0$
for $i = 1$ to $∞$
    before = Current-Time()
    while Current-Time() < $T_{target}$, re-check.
    // Measure preemption count and adjust target
    $T_{ext-preempt} = (Preemptions() - I_{begin}) \cdot T_{penalty}$
    $T_{next} = T_{begin} + T_{max} + T_{ext-preempt} + overtime$
    // Overtime-detection support
    if before ≥ $T_{next}$ and overtime = 0
        $overtime = T_{overtime}$
        $T_{next} = T_{next} + overtime$
    // If no adjustment was made, break
    if $T_{next} = T_{target}$
        return
    $T_{target} = T_{next}$
```

Fig. 3: Algorithm for applying time padding to a protected function’s execution.

Handling preemptions occurring inside the padding loop. The scheme presented above assumes that no external preemptions can occur during the the execution of the padding loop itself. However, blocking all preemptions during the padding loop will degrade the responsiveness of the system. To avoid such issues, we allow interrupts to be processed during the execution of the padding loop and update the padding time accordingly. We repeatedly update the padding time in response to preemptions until a “safe exit condition” is met where we can stop padding.

Our approach is to initially pad to the target value $T_{padded}$, regardless of how many preemptions occur. We then repeatedly increase $T_{ext-preempt}$ and pad to the new adjusted padding target until we execute a padding loop where no preemptions occur. The pseudocode of our approach is shown in Figure 3. Our technique does not leak any information about the actual runtime of the protected function as the final padding target only depends on the pattern of preemptions but not on the initial elapsed time before entering the padding loops. Note that forward progress in our padding loops is guaranteed as long as preemptions are rate limited on the cores executing protected functions.

The algorithm computes $T_{ext-preempt}$ based on observed preemptions simply by multiplying a constant $T_{penalty}$ by the number of preemptions. Since $T_{ext-preempt}$ should match the worst-case execution time of the observed preemptions, $T_{penalty}$ is the worst-case execution time of any single preemption. Like $T_{max}$, $T_{penalty}$ is machine specific and can be determined empirically from profiling data.

Handling overtimes. Our WCET estimator may miss a pathological input that causes the protected function to run for significantly more time than on other inputs. While we never
observed this in our experiments, if such a pathological input appeared in the wild, the protected function may take longer than the estimated worst-case bound and this will result in an overtime. This leaks information: the attacker learns that a pathological input was just processed. We therefore augment our technique to detect such overtimes, i.e., when the elapsed time of the protected function, taking interrupts into account, is greater than \( T_{\text{padded}} \).

One option to limit leakage when such overtimes are detected is to refuse to service such requests. The system administrator can then act by either updating the secrets (e.g., secret keys) or increasing the parameter \( T_{\text{max}} \) of the model.

We also support updating \( T_{\text{max}} \) of a protected function on the fly without restarting the running application. The padding parameters are stored in a file that has the same access permissions as the application/library containing the protected function. This file is memory-mapped when the corresponding protected function is called for the first time. Any changes to the memory-mapped file will immediately impact the padding parameters of all applications invoking the protected function unless they are in the middle of applying the estimated padding.

Note that each overtime can at most leak \( \log(N) \) bits of information, where \( N \) is the total number of timing measurements observed by the attacker. To see why, consider a string of \( N \) timing observations made by an attacker with at most \( B \) overtimes. There can be \( < N^B \) such unique strings and thus the maximum information content of such a string is \( < B \log(N) \) bits, i.e., \( < \log(N) \) bits per overtime. However, the actual effect of such leakage depends on how much entropy an application’s timing patterns for different inputs have. For example, if an application’s execution time for a particular secret input is significantly larger than all other inputs, even leaking 1 bit of information will be enough for the attacker to infer the complete secret input.

Minimizing external preemptions. Note that even though \( T_{\text{padded}} \) does not leak any sensitive information, padding to this value will incur significant performance overhead if \( T_{\text{ext-preempt}} \) is high due to frequent or long-running preemptions during the protected function’s execution. Therefore, we minimize the external events that can delay the execution of a protected function. We describe the main external sources of delays and how we deal with them in detail below.

- **Preemptions by other user processes.** Under regular circumstances, execution of a protected function may be preempted by other user processes. This can delay the execution of the protected function as long as the process is preempted. Therefore, we need to minimize such preemptions while still keeping the system usable. In our solution, we prevent preemptions by other user processes during the execution of a protected function by using a scheduling policy that prevents migrating the process to a different core and prevents other user processes from being scheduled on the same core during the duration of the protected function’s execution.

- **Preemptions by interrupts.** Another common source of preemption is the hardware interrupts served by the core executing a protected function. One way to solve this problem is to block or rate limit the number of interrupts that can be served by a core while executing a protected function. However, such a technique may make the system non-responsive under heavy load. For this reason, in our current prototype solution, we do not apply such techniques.

Note that some of these interrupts (e.g., network interrupts) can be triggered by the attacker and thus can be used by the attacker to slow down the protected function’s execution. However, in our solution, such an attack increases \( T_{\text{ext-preempt}} \), and hence degrades performance, but does not cause information leakage.

- **Paging.** An attacker can potentially arbitrarily slow down the protected function by causing memory paging events during the execution of a protected function. To avoid such cases, our solution forces each process executing a protected function to lock all of its pages in memory and disables page swapping. As a consequence, our solution currently does not allow processes that allocate more memory than is physically available in the target system to use protected functions.

- **Hyperthreading.** Hyperthreading is a technique supported by modern processor cores where one physical core supports multiple logical cores. The operating system can independently schedule tasks on these logical cores and the hardware transparently takes care of sharing the underlying physical core. We observed that protected functions executing on a core with hyperthreading enabled can encounter large amounts of slowdown. This slowdown is caused because the other concurrent processes executing on the same physical core can interfere with access to some of the CPU resources. One potential way of avoiding this slowdown is to configure the OS scheduler to prevent any untrusted process from running concurrently on a physical core with a process in the middle of a protected function. However, such a mechanism may result in high overheads due to the cost of actively unscheduling/migrating a process running on a virtual core. For our current prototype implementation, we simply disable hyperthreading as part of system configuration.

- **CPU frequency scaling.** Modern CPUs include mechanisms to change the operating frequency of each core dynamically at runtime depending on the current workload to save power. If a core’s frequency decreases in the middle of the execution of a protected function or it enters the halt state to save power, it will take longer in real-time, increasing \( T_{\text{max}} \). To reduce such variations, we disable CPU frequency scaling and low-power CPU states when a core executes a protected function.

B. Preventing leakage through shared resources

We prevent information leakage from protected functions through shared resources in two ways: isolating shared resources from other concurrent processes and lazily cleansing state left in shared resources before handing them over to other untrusted processes. Isolating shared resources of protected functions from other concurrent processes help in preventing local timing and cache attacks as well as improving performance by minimizing variations in the runtime of protected
functions.

**Isolating per-core resources.** As described earlier in Section IV-A, we disable hyperthreading on a core during a protected function’s execution to improve performance. This also ensures that an attacker cannot run spy code that snoops on per-core state while a protected function is executing. We also prevent preemptions from other user processes during the execution of protected function and thus ensure that the core and its L1/L2 caches are dedicated for the protected function.

**Preventing leakage through performance counters.** Modern hardware often contain performance counters that keep track of different performance events such as the number of cache evictions or branch mispredictions occurring on a particular core. A local attacker with access to these performance counters may infer the secrets used during a protected function’s execution. Our solution, therefore, restricts access to performance monitoring counters so that a user’s process cannot see detailed performance metrics of another user’s processes. We do not restrict, however, a user from using hardware performance counters to measure the performance of their own processes.

**Preventing leakage through L3 cache.** As L3 cache is a shared resource across multiple cores, we use page coloring to dynamically isolate the protected function’s data in the L3 cache. To support page coloring we modify the OS kernel’s physical page allocators so that they do not allocate pages having any of C reserved secure page colors, unless the caller specifically requests a secure color. Pages are colored based on which L3 cache sets a page maps to. Therefore, two pages with different colors are guaranteed never to conflict in the L3 cache in any of their cache lines.

In order to support page coloring, we disable transparent huge pages and set up access control to huge pages. An attacker that has access to a huge page can evade the isolation provided by page coloring, since a huge page can span multiple page colors. Hence, we prevent access to huge pages (transparency or by request) for non-privileged users.

As part of our implementation of page coloring, we also disable memory deduplication features, such as kernel same-page merging. This prevents a secure-colored page mapped into one process from being transparently mapped as shared into another process. Disabling memory deduplication is not unique to our solution and has been used in the past in hypervisors to prevent leakage of information across different virtual machines [39].

When a process calls a protected function for the first time, we invoke a kernel module routine to remap all pages allocated by the process in private mappings (i.e., the heap, stack, text-segment, library code, and library data pages) to pages that are not shared with any other user’s processes. We also ensure these pages have a page color reserved by the user executing the protected function. The remapping transparently changes the physical pages that a process accesses without modifying the virtual memory addresses, and hence requires no special application support. If the user has not yet reserved any page colors or there are no more remaining pages of any of her reserved page colors, the OS allocates one of the reserved colors for the user. Also, the process is flagged with a “secure-color” bit. We modify the OS so that it recognizes this flag and ensures that the future pages allocated to a private mapping for the process will come from a reserved page color for the user. Note that since we only remap private mappings, we do not protect applications that access a shared mapping from inside a protected function.

This strategy for allocating page colors to users has a minor potential downside that such a system restricts the numbers of different users’ processes that can concurrently call protected functions. We believe that such a restriction is a reasonable trade-off between security and performance.

**Lazy state cleansing.** To ensure that an attacker does not see the tainted state in a per-core resource after a protected function finishes execution, we lazily delete all per core resources. When a protected function returns, we mark the CPU as “tainted” with the user ID of the caller process. The next time the OS attempts to schedule a process from a different user on the core, it will first flush all per-CPU caches, including the L1 instruction cache, L1 data cache, L2 cache, Branch Translation Buffer (BTB), and Translation lookaside buffer (TLB). Such a scheme ensures that the overhead of flushing these caches can be amortized over multiple invocations of protected functions by the same user.

V. IMPLEMENTATION

We built a prototype implementation of our protection mechanism for a system running Linux OS. We describe the different components of our implementation below.

A. Programming API

We implement a new function annotation FIXED_TIME for the C/C++ language that indicates that a function should be protected. The annotation can be specified either in the declaration of the function or at its definition. Adding this annotation is the only change to a C/C++ code base that a programmer has to make in order to use our solution. We wrote a plugin for the Clang C/C++ compiler that handles this annotation. The plugin automatically inserts a call to the function fixed_time_begin at the start of the protected function and a call to fixed_time_end at any return point of the function. These functions protect the annotated function using the mechanisms described in Section IV.

Alternatively, a programmer can also call these functions explicitly. This is useful for protecting ranges of code within function such as the state transitions of the TLS state machine (see Section VI-B). We provide a Java native interface wrapper to both fixed_time_begin and fixed_time_end functions, for supporting protected functions written in Java.

B. Time padding

For implementing time padding loops, we read from the timestamp counter in x86 processors to collect time measurements. In most modern x86 processors, including the one we tested on, the timestamp counter has a constant frequency regardless of the power saving state of a processor. We generate pseudorandom bytes for the randomized padding step using the ChaCha/8 stream cipher [8]. We use a value of 300 µs for T_penalty as this bounds the worst-case slowdown due to a single interrupt we observed in our experiments.
Our implementation of the randomized wait operation takes an input \( X \) and simply performs \( X + c \) noops in a loop, where \( c \) is a large enough value so that the loop takes one cycle longer for each additional iteration. We observe that \( c = 46 \) is sufficient to achieve this property.

Some of the OS modifications specified in our solution are implemented as a loadable kernel module. This module supports an IOCTL call to mark a core as tainted at the end of a protected function’s execution. The module also supports an IOCTL call that enables fast access to the interrupt and context-switch count. In the standard Linux kernel, the interrupt count is usually accessed through the proc file system interface. However, such an interface is too slow for our purposes. Instead, our kernel module allocates a page of counters that is mapped into the virtual address space of the calling process. The task struct of the calling process also contains a pointer to these counters. We modify the kernel to check on every interrupt and context switch if the current task has such a page, and if so, to increment the corresponding counter in that page.

**Offline profiling.** We provide a profiling wrapper script, `fixed_time_record.sh`, that computes worst-case execution time parameters of each protected function as well as the worst-case slowdown on that function due to preemptions by different interrupts or kernel tasks.

The profiling script automatically generates profiling information for all protected functions in an executable by running the application on different inputs. During the profiling process, we run a variety of applications in parallel to create a stress-testing environment that triggers worst-case performance of the protected function. To allow the stress testers to maximally slow down the user application, we reset the scheduling parameters and CPU affinity of a thread at the start and end of every protected function. One stress tester generates interrupts at a high frequency using a simple program that generates a flood of UDP packets to the loopback network interface. We also run the `mprime` and the LINPACK benchmark to cause high CPU load and large amounts of memory contention.

**C. Prevent leakage through shared resources**

**Isolating a processor core and core-specific caches.** We disable hyperthreading in Linux by selectively disabling virtual cores. This prevents any other processes from interfering with the execution of a protected function. As part of our prototype, we also implement a simple version of the page coloring scheme described in Section [IV](#).

We prevent a user from observing hardware performance counters showing the performance behavior of other users’ processes. The `perf_events` framework on Linux mediates access to hardware performance counters. We configure the framework to allow accessing per-CPU performance counters only by the privileged users. Note that an unprivileged user can still access per-process performance counters that measure the performance of their own processes.

For ensuring that a processor core executing a protected function is not preempted by other user processes, as specified in Section [IV](#) we depend on a scheduling mode that prevents other userspace processes from preempting a protected function. For this purpose, we use the Linux `SCHED_FIFO` scheduling mode at maximum priority. In order to be able to do this, we allow unprivileged users to use `SCHED_FIFO` at priority 99 by changing the limits in the `/etc/security/limits.conf` file.

One side effect of this technique is that if a protected function manually yields to the scheduler or perform blocking operations, the process invoking the protected function may be scheduled off. Therefore, we do not allow any blocking operations or system calls inside the protected function. As mentioned earlier, we also disable paging for the processes executing protected functions by using the `mlockall()` system call with the `MCL_FUTURE`.

We detect whether a protected function has violated the conditions of isolated execution by determining whether any voluntary context switches occurred during the protected function’s execution. This usually indicates that either the protected function yield the CPU manually or performed some blocking operations.

**Flushing shared resources.** We modify the Linux scheduler to check the taint of a core before scheduling a user process on a processor core and to flush per-core resources if needed as described in Section [IV](#).

To flush the L1 and L2 caches, we iteratively read over a segment of memory that is larger than the corresponding cache sizes. We found this to be significantly more efficient than using the `WBINVD` instruction, which we observed cost as much as 300 microseconds in our tests. We flush the L1 instruction cache by executing a large number of NOP instructions.

Current implementations of Linux flush the TLB during each context switch. Therefore, we do not need to separately flush them. However, if Linux starts leveraging the PCID feature of x86 processors in the future, the TLB would have to be flushed explicitly. For flushing the BTB, we leveraged a “branch slide” consisting of alternating conditional branch and NOP instructions.

**VI. Evaluation**

To show that our approach can be applied to protect a wide variety of software, we have evaluated our solution in three different settings and found that our solution successfully prevents local and remote timing attacks in all of these settings. We describe the settings in detail below.

**Encryption algorithms implemented in high level interpreted languages like Java.** Traditionally, cryptographic algorithms implemented in interpreted languages like Java have been harder to protect from timing attacks than those implemented in low level languages like C. Most interpreted languages are compiled down to machine code on-the-fly by a VM using Just-in-Time (JIT) code compilation techniques. The

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JIT compiler often optimizes the code non-deterministically to improve performance. This makes it extremely hard for a programmer to reason about the transformations that are required to make a sensitive function’s timing behavior secret-independent. While developers writing low level code can use features such as in-line assembly to carefully control the machine code of their implementation, such low level control is simply not possible in a higher level language.

We show that our techniques can take care of these issues. We demonstrate that our defense can make the computation time of Java implementations of cryptographic algorithms independent of the secret key with minimal performance overhead.

**Cryptographic operations and SSL/TLS state machine.** Implementations of cryptographic primitives other than the public/private key encryption or decryption routines may also suffer from side channel attacks. For example, a cryptographic hash algorithm like SHA-1 takes different amount of time depending on the length of the input data. In fact, such timing variations have been used as part of several existing attacks against SSL/TLS protocols (e.g., Lucky 13). Also, the time taken to perform the computation for implementing different stages of the SSL/TLS state machine may also be dependent on the secret key.

We find that our protection mechanism can protect cryptographic primitives like hash functions as well as individual stages of the SSL/TLS state machine from timing attacks while incurring minimal overhead.

**Sensitive data structures.** Besides cryptographic algorithms, timing channels also occur in the context of different data structure operations like hash table lookups. For example, hash table lookups may take different amount of time depending on how many items are present in the bucket where the desired item is located. It will take longer time to find items in buckets with higher number of items than in the ones with less items. This signal can be exploited by an attacker to cause denial of service attacks [22]. We demonstrate that our technique can prevent timing leaks using the associative arrays in C++ STL, a popular hash table implementation.

**Experiment setup.** We perform all our experiments on a machine with 2.3GHz Intel Xeon E5-2630 CPUs organized in 2 sockets each containing 6 physical cores unless otherwise specified. Each core has a 32KB L1 instruction cache, a 32KB L1 data cache, and a 256KB L2 cache. Each socket has a 15MB L3 cache. The machine has a total of 64GB of RAM.

For our experiments, we use OpenSSL version 1.0.11 and Java version BouncyCastle 1.52 (beta). The test machine runs Linux kernel version 3.13.11.4 with our modifications as discussed in Section V.

**A. Security evaluation.**

**Preventing a simple timing attack.** To determine the effectiveness of our safe padding technique, we first test whether our technique can protect against a large timing channel that can distinguish between two different inputs of a simple function. To make the attacker’s job easier, we craft a simple function that has an easily observable timing channel—the function executes a loop for 1 iteration if the input is 0 and 11 iterations otherwise. We use the x86 loop instruction to implement the loop and just a single nop instruction as the body of the loop. We assume that the attacker calls the protected function directly and measures the value of the timestamp counter immediately before and after the call. The goal of the attacker is to distinguish between two different inputs (0 and 1) by monitoring the execution time of the function. Note that these conditions are extremely favorable for an attacker.

We found that our defense completely defeats such a distinguishing attack despite the highly favorable conditions for the attacker. We also found that the timing randomization step (described in Section IV-A) is critical for such protection and a naive padding loop with any timing randomization step indeed leaks information. Figure 4(A) shows the distributions of observed runtimes of the protected function on inputs 0 and 1 with no defense applied. Figure 4(B) shows the runtime distributions where padding is added to reach \( T_{max} = 5000 \) cycles \((\approx 2.17 \mu s)\) without the time randomization step. In both cases, it can be seen that the observed timing distributions for the two different inputs are clearly distinguishable. Figure 4(C) shows the same distributions when \( m = 5 \) rounds of timing randomization are applied along with time padding. In this case, we are no longer able to distinguish the timing distributions.

We quantify the possibility of success for a distinguishing
attack in Figure 5 by plotting the variation of empirical statistical distance between the observed distributions as the amount of padding noise added is changed. The statistical distance is computed using the following formula.

\[ d(X, Y) = \frac{1}{2} \sum_{i \in \Omega} |P[X = i] - P[Y = i]| \]

We measure the statistical distance over the set of observations that are within the range of 50 cycles on either side of the median (this contains nearly all observations.) Each distribution consist of around 600 million observations.

The dashed line in Figure 5 shows the statistical distance between two different instances of the test function with 0 as input. The solid line shows the statistical distance where one instance has 0 as input and the other has 1. We observe that the attack can be completely prevented if at least 2 rounds of noise are used.

**Preventing timing attack on RSA decryption** We next evaluate the effectiveness of our time padding approach to defeat the timing attack by Brumley et al. [15] against unblinded RSA implementations. Blinding is an algorithmic modification to RSA that uses randomness to prevent timing attacks. To isolate the impact of our specific defense, we apply our defense to the RSA implementation in OpenSSL 1.0.1h with such constant time defenses disabled. In order to do so, we configure OpenSSL to disable blinding, use the non-constant time exponentiation implementation, and use the non-word-based Montgomery reduction implementation. We measure the time of decrypting 256-byte messages with a random 2048-bit key. We chose messages to have Montgomery representations differing by multiples of \(2^{1016}\). Figure 6(A) shows the average observed running time for such a decryption operation, which is around 4.16 ms. The messages are displayed from left to right in sorted order of how many Montgomery reductions occur during the decryption. Each message was sampled roughly 8,000 times and the samples were randomly split into 4 sample sets. As observed by Brumley et al. [15], the number of Montgomery reductions can be roughly determined from the running time of an unprotected RSA decryption. Such information can be used to derive full length keys.

We then apply our defense to this decryption with \(T_{\text{max}}\) set to \(9.68 \times 10^9\) cycles \(\approx 4.21\) ms. One timer interrupt is guaranteed to occur during such an operation, as timer interrupts occur at a rate of 250/s on our target machine. We collect 30 million measurements and observe a multi-modal padded distribution with four narrow, disjoint peaks corresponding to the padding algorithm using different \(T_{\text{ext-preempt}}\) values for 1, 2, 3, and 4 interrupts respectively. The four peaks represent, respectively, 94.0\%, 5.8\%, 0.6\%, and 0.4\% of the samples. We did not observe that these probabilities vary across different messages. Hence, in Figure 6(B), we show the average observed time considering only observations from within the first peak. Again, samples are split into 4 random sample sets, each key is sampled around 700,000 times. We observe no message-dependent signal.

**Preventing cache attacks on AES encryption.** We next verify that our system protects against local cache attacks. Specifically, we measured the effectiveness of our defense against the PRIME+PROBE attack by Osvik et.al [35] on the software implementation of AES encryption in OpenSSL. For our tests, we apply the attack on only the first round of AES instead of the full AES to make the conditions very favorable to the attacker as subsequent rounds of AES add more noise to the cache readings. In this attack, the attacker first primes the cache by filling a selection of cache sets with the attacker’s memory lines. Next, the attacker coerces the victim process to perform an AES encryption on a chosen plaintext on the same processor core. Finally, the attacker reloads the memory lines it used to fill the cache sets prior to the encryption. This allows the attacker to detect whether the reloaded lines were still cached by monitoring timing or performance counters and thus infer which memory lines were accessed during the AES encryption operation.

On our test machine, the OpenSSL software AES imple-
execution is negligible due to our modifications to the Linux kernel described in Section [V].

Microbenchmarks: cryptographic operations in multiple languages. We perform a set of microbenchmarks that test the impact of our solution on individual operations such as RSA and ECDSA signing in the OpenSSL C library and in the BouncyCastle Java library. In order to apply our defense to BouncyCastle, we constructed JNI wrapper functions that call the fixed_time_begin and fixed_time_end functions. Since both libraries implement RSA blinding to defend against timing attacks, we disable RSA blinding when applying our defense.

The results of the microbenchmarks are shown in Table III. Note that the delays experienced in any real applications will be significantly less than these micro benchmarks as real applications will also perform some I/O operations that will amortize the performance overhead.

For OpenSSL, our solution adds between 3% (for RSA) and 71% (for ECDSA) to the cost of computing a signature on average. However, we offer significantly reduced tail latency for RSA signatures. This behavior is caused by the fact that OpenSSL regenerates the blinding factors every 32 calls to the signing function to amortize the performance cost of generating the blinding factors.

Focusing on the BouncyCastle results, our solution results in a 2% decrease in cost for RSA signing and a 63% increase in cost for ECDSA signing, compared to the stock BouncyCastle implementation. We believe that this increase in cost for ECDSA is justified by the increase in security, as the stock BouncyCastle implementation does not defend against local timing attacks. Furthermore, we believe that some optimizations, such as configuring the Java VM to schedule garbage collection outside of protected function executions, could reduce this overhead.

Macrobenchmark: protecting the TLS state machine. We applied our solution to protect the server-side implementation of the TLS connection protocol in OpenSSL. The TLS protocol is implemented as a state machine in OpenSSL, and this presented a challenge for applying our solution which is defined in terms of protected functions. Additionally, reading and writing to a socket is interleaved with cryptographic operations in the specification of the TLS protocol, which conflicts with our solution’s requirement that no blocking I/O may be performed within a protected function.
We addressed both challenges by generalizing the notion of a protected function to that of a protected interval, which is an interval of execution starting with a call to fixed_time_begin and ending with fixed_time_end. We then split an execution of the TLS protocol into protected intervals on boundaries defined by transitions of the TLS state machine and on low-level socket read and write operations. To achieve this, we first inserted calls to fixed_time_begin and fixed_time_end at the start and end of each state within the TLS state machine implementation. Next, we modified the low-level socket read and socket write OpenSSL wrapper functions to end the current interval, communicate with the socket, and then start a new interval. Thus divided, all cryptographic operations performed inside the TLS implementation are within a protected interval. Each interval is uniquely identifiable by the name of the current TLS state concatenated with an integer incremented every time a new interval is started within the same TLS state (equivalently, the number of socket operations that occurred so far during the state.)

The advantage of this strategy is that, unlike any prior defenses, it protects the entire implementation of the TLS state machine from any form of timing attack. However, such protection schemes may incur additional overheads due to protecting parts of the protocol that may not be vulnerable to timing attacks because they do not work with secret data.

We evaluate the performance of the fully protected TLS state machine as well as an implementation that only protects the public key signing operation. The results are shown in Table II. We observe an overhead of less than 5% on connection latency even when protecting the full TLS protocol.

**Prototyping sensitive data structures.** We measured the overhead of applying our approach to protect the lookup operation of the C++ STL unordered_map. For this experiment, we populate the hash map with 1 million 64-bit integer keys and values. We assume that the attacker cannot insert elements in the hash map or cause collisions. The average cost of performing a lookup of a key present in the map is 0.173 $\mu$s without any defense and 2.46 $\mu$s with our defense applied. Most of this overhead is caused by the fact that the worst-case execution time of the lookup operation is significantly larger than the average-case, the profiled worst-case execution time of the lookup when interrupts do not occur is 1.32 $\mu$s at $\kappa = 10^{-5}$. Thus, any timing channel defense will cause the lookup to take at least 1.32 $\mu$s. The worst-case execution estimate of the lookup operation increases to 13.3 $\mu$s when interrupt cases are not excluded, hence our scheme benefits significantly from adapting to interrupts during padding for this example. Another major part of the overhead of our solution (0.710 $\mu$s) comes from the randomization step to ensure safe padding. As we described earlier in Section VI-A, the randomization step is crucial to ensure that there is no timing leakage.

**Hardware portability.** Our solution is not specific to any particular hardware. It will work on any hardware that supports standard cache hierarchy and where page coloring can be implemented. To test the portability of our solution, we executed some of the benchmarks mentioned in Sections VI-A and VI-B on a 2.93 GHz Intel Xeon X5670 CPU. We confirmed that our solution successfully protects against the local and remote timing attacks on that platform too. The relative performance overheads were similar to the ones reported above.

### VII. Limitations

**No system calls inside protected functions.** Our current prototype does not support protected functions that invoke system calls. A system call can inadvertently leak information to an attacker by leaving state in shared kernel data structures, which an attacker might indirectly observe by invoking the same system call and timing its duration. Alternatively, a system call might access regions of the L3 cache that can be snooped by an attacker process.

The lack of system call support turned out to be not a big issue in practice as our experiments so far indicate that system calls are rarely used in functions dealing with sensitive data (e.g., cryptographic operations). However, if needed in future, one way of supporting system calls inside protected functions
while still avoiding this leakage is to apply our solution to the kernel itself. For example, we can pad any system calls that modify some shared kernel data structures to their worst case execution times.

**Indirect timing variations in unprotected code.** Our approach does not currently defend against timing variations in the execution of non-sensitive code segments that might get indirectly affected by a protected function’s execution. For example, consider the case where a non-sensitive function from a process gets scheduled on a processor core immediately after another process from the same user finishes executing a protected function. In such a case, our solution will not flush the state of per-core resources like L1 cache as both these processes belong to the same user. However, if such remnant cache state affects the timing of the non-sensitive function, an attacker may be able to observe these variations and infer some information about the protected function.

Note that currently there are no known attacks that could exploit this kind of leakage. A conservative approach that prevents such leakages is to flush all per-cpu resources at the end of each protected function. This will, of course, result in higher performance overheads. The costs associated with cleansing different types of per-cpu resources are summarized in Table 1.

**Leakage due to fault injection.** If an attacker can cause a process to crash in the middle of a protected function’s execution, the attacker can potentially learn secret information. For example, consider a protected function that first performs a sensitive operation and then parses some input from the user. An attacker can learn the duration of the sensitive operation by providing a bad input to the parser that makes it crash and measuring how long it takes the victim process to crash.

Our solution, in its current form, does not protect against such attacks. However, this is not a fundamental limitation. One simple way of overcoming these attacks is to modify the OS to apply the time padding for a protected function even after it has crashed as part of the OS’s cleanup handler. This can be implemented by modifying the OS to keep track of all processes that are executing protected functions at any given point of time and their respective padding parameters. If any protected function crashes, the OS cleanup handler for the corresponding process can apply the desired amount of padding.

**VIII. RELATED WORK**

**A. Defenses against remote timing attacks**

The remote timing attacks exploit the input-dependent execution times of cryptographic operations. There are three main approaches to make cryptographic operations’ execution times independent of their inputs: static transformation, application-specific changes, and dynamic padding.

**Application-specific changes.** One conceptually simple way to defend an application against timing attacks is to modify its sensitive operations such that their timing behavior is not key-dependent. For example, AES [10, 27, 30] implementations can be modified to ensure that their execution times are key-independent. Note that, since the cache behavior impacts running time, achieving secret-independent timing usually requires rewriting the operation so that its memory access pattern is also independent of secrets. Such modifications are application specific, hard to design, and very brittle. By contrast, our solution is completely independent of the application and the programming language.

**Static transformation.** An alternative approach to prevent remote attacks is to use static transformations on the implementation of the cryptographic operation to make it constant time. One can use a static analyzer to find the longest possible path through the cryptographic operation and insert padding instructions that have no side-effects (like NOP) along other paths so that they take the same amount of time as the longest path [17, 20]. While this approach is generic and can be applied to any sensitive operation, it has several drawbacks. In modern architectures like x86, the execution time of several instructions (e.g., the integer divide instruction and multiple floating-point instructions) depend the value of the input of these instructions. This makes it extremely hard and time consuming to statically estimate the execution time of these instructions. Moreover, it is very hard to statically predict the changes in the execution time due to internal cache collisions in the implementation of the cryptographic operation. To avoid such cases, in our solution, we use dynamic offline profiling to estimate the worst-case runtime of a protected function. However, such dynamic techniques suffer from incompleteness i.e. they might miss worst-case execution times triggered by pathological inputs.

**Dynamic padding.** Dynamic padding techniques add a variable amount of padding to a sensitive computation that depends on the observed execution time of the computation in order to mitigate the timing side-channel. Several prior works [6, 18, 24, 31, 47] have presented ways to pad the execution of a black-box computation to certain predetermined thresholds and obtain bounded information leakage. Zhang et al. designed a new programming language that, when used to write sensitive operations, can enforce limits on the timing information leakage [48]. The major drawback of existing dynamic padding schemes is that they incur large performance overhead. This results from the fact that their estimations of the worst-case execution time tend to be overly pessimistic as it depends on several external parameters like OS scheduling, cache behavior of the simultaneously running programs, etc. For example, Zhang et al. [47] set the worst-case execution time to be 300 seconds for protecting a Wiki server. Such overly pessimistic estimates increase the amount of required padding and thus results in significant performance overheads (90 – 400% in macro-benchmarks [47]). Unlike existing dynamic padding schemes, our solution incurs minimal performance overhead and protects against both local and remote timing attacks.

**B. Defenses against local attacks**

Local attackers can also perform timing attacks, hence some of the defenses provided in the prior section may also be used to defend against some local attacks. However, local attackers also have access to shared hardware resources that contain information related to the target sensitive operation. The local attackers also have access to fine-grained timers.

A common local attack vector is to probe a shared hardware
resource, and then, using the fine-grained timer, measure how long the probe took to run. Most of the proposed defenses to such attacks try to either remove access to fine-grained timers or isolate access to the shared hardware resources. Some of these defenses also try to minimize information leakage by obfuscating the sensitive operation’s hardware access patterns. We describe these approaches in detail below.

**Removing fine-grained timers.** Several prior projects have evaluated removing or modifying time measurements taken on the target machine \[33, 34, 42\]. Such solutions are often quite effective at preventing a large number of local side channel attacks as the underlying states of most shared hardware resources can only be read by accurately measuring the time taken to perform certain operations (e.g., read a cache line).

However, removing access to wall clock time is not sufficient for protecting against all local attackers. For example, a local attacker executing multiple probe threads can infer time measurements by observing the scheduling behavior of the threads. Custom scheduling schemes (e.g., instruction-based scheduling) can eliminate such an attack \[33\] but implementing these defenses require major changes to the OS scheduler. In contrast, our solution only requires minor changes to the OS scheduler and protects against both local and remote attackers.

**Preventing sharing of hardware state across processes.** Many proposed defenses against local attackers prevent an attacker from observing state changes to shared hardware resources caused by a victim process. We divide the proposed defenses into five categories and describe them next.

**Resource partitioning.** Partitioning shared hardware resources can defeat local attackers, as they cannot access the same partition of the resource as a victim. Kim et al. \[28\] present an efficient management scheme for preventing local timing attacks across virtual machines (VMs). Their technique locks memory regions accessed by sensitive functions into reserved portions of the L3 cache. This scheme can be more efficient than page coloring. Such protection schemes are complementary to our technique. For example, our solution can be modified to use such a mechanism instead of page coloring to dynamically partition the L3 cache.

Some of the other resource partitioning schemes (e.g., Ristenpart et al. \[21\]) suggest allocating dedicated hardware to each virtual machine instance to prevent cross-VM attacks. However, such schemes are wasteful of hardware resources as they decrease the amount of resources available to concurrent processes. By contrast, our solution utilizes the shared hardware resources efficiently as they are only isolated during the execution of the protected functions. The time a process spends executing protected functions is usually much smaller than the time it spends in non-sensitive computations.

**Limiting concurrent access.** If gang scheduling \[28\] is used or hyperthreading is disabled, an attacker can only observe per-CPU resources when it has preempted a victim. Hence, reducing the frequency of preemptions reduces the feasibility of cache-attacks on per-CPU caches. Varadarajan et al. \[41\] propose using minimum runtime guarantees to ensure that a VM is not preempted too frequently. However, as noted in \[41\], such a scheme is very hard to implement in a OS scheduler as, unlike a hypervisor scheduler, an OS scheduler must deal with an unbounded number of processes.

**Custom hardware.** Custom hardware can be used to obfuscate and randomize the victim process’s usage of the hardware. For example, Wang et al. \[43, 44\] proposed new ways of designing caches that ensures that no information about cache usage is shared across different processes. However such schemes have limited practical usage as they, by design, cannot be deployed on off-the-shelf commodity hardware.

**flushing state.** Another class of defenses ensure that the state of any per-CPU hardware resources are cleared before transferring them from one process to another. Düpapel, by Zhang et al. \[50\], flushes per-CPU L1 and (optionally) L2 caches periodically in a multi-tenant VM setting. Their solution also requires the hyperthreading to be disabled. They report around 7% overheads on regular workloads. In essence, this scheme is similar to our solution’s technique of flushing per-CPU resources in the OS scheduler. However, unlike Düpapel, we flush the state lazily only when a context switch to a different user process than the one executing a protected operation occurs. Also, Düpapel only protects against local cache attacks. We protect against both local and remote timing and cache attacks while still incurring less overhead than Düpapel.

**Application transformations.** Sensitive operations like sensitive computations in different programs can also be modified to exhibit either secret-independent or obfuscated hardware access patterns. If the access to the hardware is independent of secrets, then an attacker cannot use any of the state leaked through shared hardware to learn anything meaningful about the sensitive operations. Several prior projects have shown how to modify AES implementations to obfuscate their cache access patterns \[9, 10, 13, 35, 40\]. Similarly, recent versions of OpenSSL use a specifically modified implementation of RSA that ensures secret-independent cache accesses. Some of these transformations can also be applied dynamically. For example, Crane et al. \[21\] implement a system that dynamically applies cache-access obfuscating transformations to an application at runtime.

However, these transformations are specific to particular cryptographic operations and are very hard to implement and maintain correctly. For example, 924 lines of assembly code had to be added to OpenSSL to implement make the RSA implementation’s cache accesses secret-independent.

**IX. Conclusion**

We presented a low-overhead, cross-architecture defense that protects applications against both local and remote timing attacks with minimal application code changes. Our experiments and evaluation also show that our defense works across different applications written in different programming languages.

Our solution defends against both local and remote attacks by using a combination of two main techniques: (i) a time padding scheme that only takes secret-dependent time variations into account, and (ii) preventing information leakage via shared resources such as the cache and branch prediction buffers. We demonstrated that applying small time pads accurately is non-trivial because the timing loop itself may leak.
information. We developed a method by which small time pads can be applied securely. We hope that our work will motivate application developers to leverage some of our techniques to protect their applications from a wide variety of timing attacks. We also expect that the underlying principles of our solution will be useful in future work protecting against other forms of side channel attacks.

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