Valkyrie: A Response Framework to Augment Runtime Detection of Time-Progressive Attacks

Nikhilesh Singh[†][®] System Security Lab Technische Universität Darmstadt Darmstadt, Germany nikhilesh.singh@tu-darmstadt.de Chester Rebeiro Dept. of Computer Science & Engg. Indian Institute of Technology Madras Chennai, India chester@cse.iitm.ac.in

Abstract—A popular approach to detect cyberattacks is to monitor systems in real-time to identify malicious activities as they occur. While these solutions aim to detect threats early, minimizing damage, they suffer from a significant challenge due to the presence of false positives. False positives have a detrimental impact on computer systems, which can lead to interruptions of legitimate operations and reduced productivity. Most contemporary works tend to use advanced Machine Learning and AI solutions to address this challenge. Unfortunately, false positives can, at best, be reduced but not eliminated. In this paper, we propose an alternate approach that focuses

on reducing the impact of false positives rather than eliminating them. We introduce Valkyrie, a framework that can enhance any existing runtime detector with a post-detection response. Valkyrie is designed for time-progressive attacks, such as micro-architectural attacks, rowhammer, ransomware, and cryptominers, that achieve their objectives incrementally using system resources. As soon as an attack is detected, Valkyrie limits the allocated computing resources, throttling the attack, until the detector's confidence is sufficiently high to warrant a more decisive action. For a false positive, limiting the system resources only results in a small increase in execution time. On average, the slowdown incurred due to false positives is less than 1% for single-threaded programs and 6.7% for multithreaded programs. On the other hand, attacks like rowhammer are prevented, while the potency of micro-architectural attacks, ransomware, and cryptominers is greatly reduced.

Index Terms—Post-Detection Response, False Positives, Time-Progressive Attacks, Runtime Attack Detection.

I. INTRODUCTION

The last few years have seen an unprecedented rise in malware that threatens the security of computing systems. Sideby-side, new malware classes such as ransomware, microarchitectural attacks, cryptominers, and rowhammer have evolved to be extremely potent attack vectors. Ransomware encrypts the contents of a victim's file system and is growing at an alarming rate of 27% per year [30]. Similarly, with the increased usage of cryptocurrencies, cryptomining malware has also grown significantly, by more than six times in 2023 [59]. Micro-architectural attacks [28] and rowhammer [34] are new attack vectors that utilize inherent weaknesses in the hardware, making them difficult to defend against. While microarchitectural attacks leak sensitive information through shared hardware resources, rowhammer attacks are capable of flipping bits in memory without accessing them.

A common feature among all of these attacks is that they progress incrementally with execution time. For example, if ransomware executes for a longer duration, it can encrypt more files. Thus, the progress of the ransomware attack increases with execution time. Similarly, if executed for a longer duration, cryptominers are likely to compute more hashes, micro-architectural attacks can leak more information, while rowhammer is likely to flip more bits in memory. These attacks, which we call *time-progressive attacks*, achieve their objectives gradually during their execution.

An extensively studied approach to counter time-progressive attacks at runtime is based on the program execution behavior [12], [19], [23], [32], [38], [46]–[49], [53], [64], [69]. A typical runtime detector profiles features of executing programs to train a Machine Learning (ML) model [10], [12], [23], [32], [38], [46]–[49], [64] to identify patterns unique to time-progressive attacks. For example, hardware performance counters (HPCs) present in processors [12], [25], [32], [38], [46]–[49], [64], system-level APIs [10], [33], [45], and network activity [27], [33] are periodically measured and used by trained models to detect an ongoing attack. Such detection approaches can be easily adapted to support new attacks, while at the same time, applied at various levels of the computing stack, such as the network, Operating System (OS), and hardware [33].

A limitation of these ML-based detectors is that they are susceptible to false positives. As a result, benign programs are classified malicious. Existing works address these false positives by using more sophisticated detection models [23], [32], [33]. For example, Gulmezoglu *et al.* [32] use unsupervised deep learning techniques, while Karapoola *et al.* [33] employ a multi-level mixture of experts model for detection. However, none of these solutions can completely eliminate false positives in real-world deployments [24], [36], [70]. For instance, [12] implements perceptrons and has up to 7% false positives, while [48] which uses more sophisticated machine learning models, has under 3% false positives for detecting

[†]The author was associated with the Indian Institute of Technology Madras during the work.

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micro-architectural attacks.

False positives in attack detection can adversely impact operations. For instance, a high number of false positives in the alerts raised by the detector at the retail network Target, led to alerts being ignored by the security team. This eventually resulted in one of the most prominent cyber attacks in recent years [11]. Instead of alerting users about ongoing attacks, another option is to terminate programs that are classified malicious. This would result in a large number of falsely classified programs being prematurely terminated. In some cases [49], [69], the detected programs can be migrated to a different execution environment, resulting in significant overheads. Thus, there is a pressing need to design efficient responses, following a detection.

Post-detection response strategies for time-progressive attacks have two critical requirements. R1: The response should throttle attacks and minimize their progress. R2: The response should minimally affect the execution of benign programs when falsely classified. Throttling attacks and minimizing their progress requires timely detection and termination. In contrast, reducing the adverse effects of benign programs necessitates improving the efficacy of detection, primarily minimizing false positives. However, the higher detection efficacy would require more complex detection models or a larger number of runtime measurements, causing delays in thwarting attacks.

Most existing works, unfortunately, target satisfying R1 but not R2, hampering the usability of the solution. For instance, even a low false-positive rate, of say, 3% [48], would mean that 3 out of every 100 programs, on average, would be terminated prematurely. Addressing this limitation requires either the elimination of false positives or a reduction in the impact of false positives. Since the elimination of false positives with present-day ML models is challenging, it is essential to focus on minimizing the impact of false positives. Thus, we pose the following research question in this work: *can we design post-detection response mechanisms for runtime detectors that satisfy* R1 and R2, thwarting attacks while minimizing the adverse impacts of false positives?

A characteristic feature of all time-progressive attacks is that they require system resources, such as CPU, memory, network, or the file system, for successful execution. Limiting these resources would result in slowing down the attack's progress. For example, limiting the time a ransomware executes in the CPU, restricting the memory allocated to the process, or restricting file system access can slow down the rate at which files are encrypted. We use this observation to present Valkyrie, a framework to augment detectors with post-detection response strategies ¹. Designed to handle the adverse impacts of false positives, Valkyrie augments a detector that periodically provides an inference. Programs that are detected malicious are terminated only if the detection has sufficient *detection efficacy*. If the detection efficacy is not achieved, detected programs are slowed down by throttling system resources

needed for their execution. For an attack, the slowdown would reduce its progress, while for a false positive, there is a temporary slowdown. This is less adverse than termination. Thus, the choice of detection efficacy affects the slowdown of false positives as well as the rate at which attacks are stymied. We define detection efficacy as a metric that quantifies the capability of the detector to classify benign and malicious program behavior. It can be represented by model evaluation metrics such as F1-score and false positive rate (FPR). Users can specify constraints regarding the detection efficacy, based on the application. Once this efficacy is reached, the program is terminated only if it continues to be classified as malicious. On the other hand, if the program is classified as benign a false positive – then its resources are gradually restored. Thus, Valkyrie provides a response mechanism ensuring that benign programs do not face premature termination (R2) while attacks are throttled (R1).

Following are the key contributions of the paper.

- We present Valkyrie, a response framework that augments detection countermeasures for time-progressive attacks to minimize the impacts of false positives while ensuring that attacks get throttled. Valkyrie slows down the progress of attacks by restricting system resources and terminates a detected process only when the detector achieves sufficient detection efficacy specified by the user.
- The implementation of Valkyrie requires minimal changes and can be plugged into any detector. We demonstrate Valkyrie by augmenting multiple detectors against various time-progressive attacks. We present case studies involving various micro-architectural attacks, such as Prime+Probe on the L1 Data [50], L1 Instruction [9], and LLC caches [42], [66]; L1 and TLB Evict+Time attacks [29], [50]; and Fill-and-Forward Timed Speculative Attack on Load-Store Buffer [22]. Similarly, we also evaluate Valkyrie with rowhammer [1], [34], ransomware [3]–[7], and cryptominers [52].
- We mathematically quantify the slowdowns induced by Valkyrie when benign processes are falsely classified. We present an empirical evaluation of these slowdowns with multiple benign benchmark suites, including SPEC-2017 [20], SPEC-2006 [60], SPECViewperf-13 [2], STREAM [43], and multi-threaded SPEC-2017 [20]. The average slowdowns are 1% for single-threaded and 6.7% for multi-threaded programs across different evaluation systems. Additionally, Valkyrie also supports a configurable upper limit for maximum slowdowns due to resource throttling.

The rest of the paper is organized as follows. Section II presents the necessary background on time-progressive attacks and their detection. We provide an overview of existing post-detection approaches in Section III. Section IV describes the motivation for Valkyrie and presents an overview of the framework. In Sections V and VI, we discuss the design of Valkyrie in detail and demonstrate the utility of Valkyrie by augmenting several detectors for various time-progressive

¹The relevant code and data associated with Valkyrie are maintained at https://bitbucket.org/casl/valkyrie/src/main/

TABLE I: Existing runtime detection countermeasures and their post-detection responses along with the reported false positives. [Req: Rquirement; \bigcirc : requirement not satisfied, \bigcirc : requirement partially satisfied, \bigcirc : requirement satisfied].

Post-Detection	Banans	Req.		False positives	
Response	rapers	R1	R2	reported	
	Alam et al. [12]			5-7%	
	Briongos et al. [19]			1.6-4.3%	
	Chiapetta et al. [23]			Not reported	
	Gulmezoglu et al. [32]			0.21%	
	Mushtaq et al. [46]			1-30%	
	Mushtaq et al. [47]		\cap	5%	
Not Specified	Wang <i>et al.</i> [64]			upto 13.6%	
Not Specificu	Karapoola et al. [33]		\cup	0.01%	
	Ahmed et al. [10]			0.58%	
	Vig et al. [63]			1%	
	Pott et al. [56]			0.2%	
	Tahir <i>et al.</i> [61]			0.25%	
	Mani et al. [40]	1		0.2-3.8%	
Warning	Kulah <i>et al.</i> [38]	$ $ \bigcirc	0	Not reported	
Migration	Zhang et al. [69]			Not reported	
wingration	Nomani et al. [49]		V	Not reported	
Termination	Mushtaq et al. [48]			1-3%	
Terminution	Payer [53]		\bullet	Not reported	
DRAM	Aweke et al. [14]			1%	
responses	Yaglikçi et al. [65]			0.01%	
Systematic	Valkyria (this paper			Sama as	
throttling and	augmented with any		•	Same as	
eventual	detector)			dataatar	
termination	detector)			uciccioi	

attacks as case studies, respectively. Section VII presents a discussion on the limitations of Valkyrie, while Section VIII concludes the paper.

II. BACKGROUND

A. Time-Progressive Attacks

Time-progressive attacks use system resources such as CPU, memory, network, kernel APIs, or the filesystem to achieve their objectives incrementally with execution. For example, consider cryptominers [52]. These attacks aim to mine cryptocurrency, which involves a computationally intensive challenge, such as recovering the input of a hash function from a given output. The longer the cryptominer executes, the more challenges can be solved to mine cryptocurrency. Similarly, micro-architectural attacks rely on the execution time measurements to glean information. When given a longer time to execute, these attacks can collect more measurements and, in turn, leak more bits of information. Restricting the system resources such as CPU time, memory, network and filesystem can, thus, impede the progress of time-progressive attacks. In this paper, we make use of this dependence of the attack's progress on the system resources to design Valkyrie.

B. Runtime Detection of Attacks

Runtime detection of time-progressive attacks typically involves detection models trained on measurements representing program behavior. These measurements are captured using tools such as the Linux Perf tool [55], which captures the CPU's hardware performance counters (HPCs); Microsoft ProcMon [45], which captures the operating system (OS) events; or Wireshark [27], which captures network behavior. Machine Learning (ML) based detection models such as SVM [47], XGBoost [33] and artificial neural networks (ANNs) [49] are trained on such measurements from benign and malicious programs. After training, the detector is deployed to classify processes using the measurements that are continuously captured for each process at runtime.

Several existing works have demonstrated the efficacy of such runtime detectors to identify time-progressive attacks [12], [19], [23], [32], [38], [46]–[49], [53], [64], [69]. Unfortunately, all of these approaches have been shown to be susceptible to false positives [24], [36], [70], which impact their usability. For this work, the comparative assessment of different types of measurements and detectors is not relevant. Rather, we are interested in post-detection response strategies. We discuss this in the next section.

III. EXISTING POST-DETECTION APPROACHES

Table I presents the post-detection response strategies followed in existing runtime detection countermeasures along with the reported false positive rate (FPR) of each detector. The FPR represents the benign programs that are affected by the response. We evaluate these post-detection responses with respect to the requirements R1 and R2 described in Section I. Most existing runtime detectors [10], [12], [19], [23], [32], [33], [40], [46], [47], [56], [61], [63], [64] for time-progressive attacks do not specify any post-detection response. Works such as Kulah *et al.* [38] respond with a warning to the user once a process is classified malicious. Since handling the detection requires a vigilant user, it is challenging to guarantee either of the requirements R1 or R2 with these approaches.

A promising response strategy for micro-architectural attacks is to migrate the detected process to a different CPU core or another virtual machine (VM). While this approach satisfies both R1 and R2, it has two key limitations. First, migration is applicable only against contention-based microarchitectural attacks [49], [69] such as cache attacks in cloud infrastructure [13], [54]. Second, migration of processes across VMs can induce high overheads. For instance, a process that is falsely classified malicious throughout its execution by [49] can incur up to 50% performance overheads due to migration across CPU cores.

The detection countermeasure presented in Payer [53] requires users to select between termination or a reduction in the execution priority of attacks like rowhammer [34]. While termination satisfies R1 but not R2, reducing the execution priority may not satisfy R1 as it can allow attacks to execute endlessly. Further, relying on users to respond after detection also affects the consistency of the approach. Mushtaq *et al.* [48] discuss the challenge of false positives in microarchitectural attack detection and attempt to address it with a post-detection response. Rather than terminating a process right after detection, this solution terminates a process only when it is classified malicious three times consecutively. While such an approach reduces the number of benign processes that are falsely terminated from 5% to under 3% (R2), the choice



Fig. 1: Detection efficacy of various models similar to existing works with respect to the number of runtime measurements captured by the detector and elapsed time. The user of a detection solution can specify the desired level of detection efficacy.

of waiting for three consecutive classifications is arbitrary and can not be generalized across detectors.

The authors in [14] and [65] present responses to refresh the DRAM after detecting a rowhammer attack. While these approaches satisfy both R1 and R2, the response specifically targets rowhammer and is not applicable to other attacks. Unlike the post-detection responses in existing works, Valkyrie can augment any runtime detector targeting a wide range of time-progressive attacks, making it scalable and generalizable. Once the solution is deployed, Valkyrie does not require any involvement of the user. Further, the responses from Valkyrie are not arbitrary, but are designed based on the threat level of a process and the specifications given by the user for detection efficacy and performance slowdowns.

IV. MOTIVATION AND OVERVIEW

The design of Valkyrie is based on two key observations. The first is that the efficacy of detection models increases over time with the number of captured runtime measurements of process behavior [37]. Second, time-progressive attacks are impacted by the availability of system resources, as discussed in Section II-A. In this section, we analyze these two observations to motivate the design of Valkyrie. We then describe the high-level overview of the design.

A. Detection Efficacy Over Time

To detect time-progressive attacks at runtime, measurements representing program behavior are captured periodically. A detector augmented with Valkyrie uses these measurements to provide an inference for each process at periodic intervals called a measurement epoch or an epoch. Thus, with every passing epoch, the detector accumulates a larger number of measurements to classify the process behavior. For most detection models, the detection efficacy improves with the measurements captured. Fig. 1 presents the detection efficacy of popular detection models with respect to the number of measurements captured. We use metrics such as F1-Score (Fig. 1a) and the False Positive Rate (FPR) (Fig. 1b) to represent the detection efficacy. The analysis includes small and large artificial neural networks (ANNs) similar to [12], [23], [32], [48], a Support Vector Machine (SVM) model as used in [33], [46], and an XGBoost ensemble as deployed in [33]. The small ANN has one hidden layer of 4 nodes, while the large ANN has two hidden layers of 8 nodes each. All the evaluated detectors in Fig. 1 use HPC measurements to detect ransomware programs. In these experiments, we use 67 ransomware programs from various open-source repositories [3]-[7]. Each model provides an inference after every measurement (i.e., every epoch has one additional measurement). The ANNs take a time series of HPC measurements as input to classify programs. On the other hand, the SVM and XGBoost models classify each measurement individually and infer program behavior based on the classification of majority of these measurements. For the purpose of our discussion, the comparison across these detectors is not relevant. Rather, we are interested in the change in detection efficacy over time. We observe that the efficacy of each detector improves with the number of measurements. For instance, the F1-Score of the small ANN is 0.7 with 5 measurements, which increases to 0.8 with 75 measurements. For a typical HPC monitoring tool [55] that captures hardware events every 100ms, these measurements would require 7 seconds.

We can utilize the trend that detection efficacy improves with time (Fig. 1) to determine the number and duration of measurements required to achieve a specified level of efficacy. For instance, to get an F1-Score of more than 0.9, the XGBoost detector would need 23 measurements, thus, 2.3 seconds. Similarly, an FPR of less than 10% on the same model would require at least 5 seconds of measurements. While accumulating measurements for a longer time improves the detection efficacy, it also enables the attacks to progress further. For example, by the time the ANN improves its F1-Score to 0.8, ransomware encrypting data at a rate of 11.67MB/s [3], can corrupt 81MB of data. Similarly, a microarchitectural attack that gleans data at 40KB/s [42], can extract 300KB. Thus, we need a solution that enables the detector to accumulate measurements for a longer time, thereby attaining sufficient detection efficacy while, at the same time, thwarting the progress of the attacks.

B. Resource Availability and Attack Progress

To design a post-detection response framework that thwarts the attack progress while the detector attains a specified efficacy, we evaluate the dependence of time-progressive attacks



Fig. 2: An overview of Valkyrie post-detection response framework augmenting a runtime detector. In an offline phase, users can specify the detection efficacy required based on the application, and Valkyrie determines the number of measurements required to achieve it. The detector provides an inference for a process periodically during execution, which is used by Valkyrie to determine the threat index of the process. Based on the threat index and the number of measurements, Valkyrie responds with a modification in available resources for the process or termination.

on system resources. Consider an attack that (a) recursively opens files present in the system, (b) computes the hash of each file, and (c) sends the hash and the contents of each file over the network to a colluding server. The progress of this attack can be measured by the number of bytes transmitted to the server. This is a time-progressive attack (Section II), as the number of hashes computed and bytes transmitted increases with time. The attack uses resources such as the disk to access files, memory for data and instructions, network to transmit the file contents, and CPU for execution. Table II demonstrates the effects of variation in available resources on the progress of the program. We control the system resources available to the program using management features in the Linux kernel [62].

CPU time. We quantify the CPU usage based on the fraction of time for which a program executes on the CPU core. We control this CPU time using a Cgroup-based utility [62]. As shown in Table II, reducing the CPU share to 1% can slow down the rate of progress by 99.7% with respect to the default.

Memory. We measure the available memory given to the program relative to the maximum memory space used by the program without any restrictions. We modify the available memory for a program by creating a Cgroup and assigning limits on the usable memory. This ensures that the program never exceeds the specified memory usage by forcibly invalidating the associated pages. We observe that a reduction in the available memory significantly brings down the attack progress, as shown in Table II. For instance, the attack's rate of progress slows down by 99.99% when we reduce the available memory to 93.6% of the required memory.

Network. Limiting the network bandwidth affects the transmission of file contents by the attack program to the server. To regulate the available network bandwidth, we use the Cgroup feature and specify upper bounds for the usage of network bandwidth. As shown in Table II, halving the network bandwidth slows down the rate of progress by 11.4%.

Filesystem. Modifying the rate of filesystem access affects file reading for hash computations and transmission. We control this rate by keeping track of the files opened and using signals to pause and resume execution. Changes in the rate of file accesses affect the rate of progress proportionally (Table II).

TABLE II: The rate of progress of the example time-progressive attack that recursively computes the hash of the victim's files and transmits the contents to a colluding server, with variations in the available system resources.

	Availability		Rate of Progress		
Resource	Value	% of default	Bytes transmitted (KB/second)	% slowdown	
	100% [default]	100%	225.7	_	
CPU	90%	90% 206.1		8.7%	
	50%	50%	123.6	45.2%	
	1%	1%	0.6	99.7%	
Memory	4.7M [default]	100%	225.7	-	
	4.6M	93.6%	0.087	99.96%	
	4.4M	89.4%	0.013	99.99%	
Network	1024G [default]	100%	225.7	-	
	512G	50%	200	11.4%	
	512M	$10^{-3}\%$	56.63	74.9%	
	512K	$10^{-6}\%$	0.05	99.98%	
	100 file/s	100%	225.7	_	
Filesystem	[default]	100 //	223.1		
	90 files/s	100%	200.1	11.3%	
	50 files/s	50%	113.7	49.6%	
	1 file/s	1%	2.2	99%	

We observe that different system resources influence the attack progress at varying rates. For instance, the available CPU time and the rate of file access affect the rate of progress in a proportional manner. Availability of the network bandwidth has a linear effect on the progress. On the other hand, limiting the available memory has a non-linear and sharp effect on the attack's progress. Thus, throttling the available memory can restrict the attack progress sharply while we can have a graceful decline in progress by throttling the CPU time and file accesses.

C. Valkyrie: An Overview

We have two important takeaways from the previous sections. First, a runtime detector needs to accumulate measurements for longer durations in order to improve its detection efficacy (Section IV-A). Second, restricting system resources can impede time-progressive attacks (Section IV-B). Based on these two observations, we design our post-detection response framework, Valkyrie.

Fig. 2 provides the high-level overview of Valkyrie. For each executing process, the detector augmented with Valkyrie,

provides a periodic inference. The response to these inferences depends on the expected level of detection efficacy needed by the target system. For example, critical systems necessitate termination of attacks as early as possible. A higher FPR in such systems is more easily tolerated. From Fig. 1, this would require that the detector provides its response based on fewer measurements. General purpose systems, on the other hand, are more sensitive to false positives. Therefore, detectors should terminate attacks in general purpose systems after observing larger number of measurements.

In Valkyrie, users can specify the expected detection efficacy. Based on this input Valkyrie computes the number measurements needed to achieve the specified efficacy. While the detector accumulates the required number of measurements, Valkyrie proportionally throttles the processes classified malicious by regulating the system resources, thereby reducing the attack's progress as described in Section IV-B.

To implement Valkyrie, we address the following questions.

Q1: Which system resources to throttle? The pattern of resource utilization varies from one time-progressive attack to another. For instance, ransomware has a significant dependence on the CPU as well as the file system. On the other hand, cryptominers are entirely CPU-dependent and do not use the filesystem. Thus, Valkyrie monitors processes at runtime to ensure that the system resources critical to the attack progress are throttled.

Q2: How to throttle the system resources? Once the resources to throttle are identified, we need a mechanism to (a) quantify and (b) regulate the resources. To quantify the resources available to a process, Valkyrie calculates a threat index for the process. The threat index is a value between 0 and 100 that quantifies the maliciousness of the process. A higher threat index implies a higher confidence in the process being malicious. The calculation of the threat index for a process at any instant is based on all the previous inferences from the detector. The threat index increases when the detector classifies the process as malicious and decreases when it is classified as benign. An actuator function uses the threat index to regulate the share of system resources available to the process. For example, the actuator function can use Linux kernel features to throttle CPU, memory, network, and the filesystem, as discussed in Section IV-B.

Q3: How long to throttle and when to terminate? Valkyrie regulates the resources available to the process until the detector attains the detection efficacy specified by the user. After this, the process can be terminated if classified as malicious by the detector, or its resources are restored if it is detected as a false positive (classified benign).

V. THE VALKYRIE RESPONSE MECHANISM

In this section, we discuss the design of Valkyrie with a formal description. Consider a detector \mathcal{D} augmented with Valkyrie, which uses the runtime measurements to classify process behavior. Let N* be the number of measurements required by \mathcal{D} to achieve the detection efficacy specified by the user. N* is determined offline by learning the changes in detection efficacy with respect to the number of measurements, as discussed in Section IV-A. Let t be a process executing on the system with N^t_i(< N*) measurements captured till the start of the *i*-th epoch. Based on these measurements, the detector \mathcal{D} classifies t as malicious or benign in the *i*-th epoch, represented by $\mathcal{D}(t, i) = \{\text{malicious, benign}\}.$

The set R_i^t represents the share of system resources available to process t in the *i*-th epoch, such that,

$$R_{i}^{t} = \{ r_{\text{CPU}}^{t}(i), r_{\text{mem}}^{t}(i), r_{\text{nw}}^{t}(i), r_{\text{fs}}^{t}(i) \} , \qquad (1)$$

where $r_{CPU}^{t}(i), r_{mem}^{t}(i), r_{nw}^{t}(i)$ and $r_{fs}^{t}(i)$ represent the share of CPU time, memory, network, and filesystem, respectively available to the process t in the *i*-th epoch.

Valkyrie utilizes the inference $\mathcal{D}(t, i)$ and the user specification (N^{*}) to assess the threat posed by process t. The threat assessment is used to determine a response for $\mathcal{D}(t, i)$. For instance, we can increase, decrease, or maintain the share of system resources (a subset of R_i^t) available to t, thus affecting the execution of the process.

A. Threat Assessment with Valkyrie

The threat index for the process t in the *i*-th epoch, T_i^t , is a quantification of the detector's confidence in the process being malicious. A threat index of 0 implies that the process is benign and has no restrictions on the system resources, while a threat index of 100 would result in the maximum restrictions on resources. The value of the threat index in an epoch is based on the history of the detector's inferences till that epoch. To determine the threat index, Valkyrie maintains two metrics for each process, namely, penalty (P_i^t) and compensation (C_i^t). Before the detector accumulates the required number of measurements (\mathbb{N}^*), the threat index increases by the penalty metric each time the detector classifies t as malicious (Line 11 in Algorithm 1). If the behavior of the process t improves and the detector classifies it as benign, the threat index decreases by the compensation metric (Line 15 in Algorithm 1).

To determine the values of P_i^t and C_i^t , Valkyrie uses two configurable functions. The penalty assessment function $(\mathcal{F}_n(\mathbf{P}_i^t))$ takes in the penalty value of the previous epoch and increases the penalty value if the process is classified malicious (Lines 8-11 in Algorithm 1). Similarly, the compensation assessment function $(\mathcal{F}_{c}(C_{i}^{t}))$ increases the compensation metric if $T_i^t > 0$ and the process is classified benign (Lines 13-15 in Algorithm 1). To restrict the values of P_i^t , C_i^t and T_i^t between 0 and 100, we use a clamp() function (Lines 1, 10, 14, and 16) Algorithm 1). Both these functions can have several possible realizations, such as incremental $(P_i^t = \mathcal{F}_p(P_{i-1}^t) = P_{i-1}^t + 1)$, linear $(\mathcal{F}_p(\mathbf{P}_{i-1}^t) = a\mathbf{P}_{i-1}^t + b$, where a and b are constants), or exponential $(\mathcal{F}_p(\mathbf{P}_{i-1}^t) = 2^i \mathbf{P}_{i-1}^t + 1)$. Based on these functions, the penalty and compensation metrics can grow at varying rates, which, in turn, influences the threat index (T_i^t) and the throttling of the process.

Algorithm 1: Execution of process t with a detector \mathcal{D} augmented with the Valkyrie.

- 1 Global: A process t; state(t): state of process t; $\mathcal{D}(t, i)$: online detector's inference in *i*-th epoch; R_i^t : share of resources available to t in *i*-th epoch; \mathbb{N}_i^t : measurements captured for t till *i*-th epoch; \mathbb{N}^* : number of measurements required to satisfy user specification; $\operatorname{clamp}(x) = \max(0, \min(x, 100))$.
- 2 Initial State: t is executing; state(t) =normal; $i = 0; P_i^t = C_i^t = T_i^t = N_i^t = 0;$
- 3 begin

while t is executing do 4 while $N_i^t < N^*$ do 5 i = i + 1 and Update N_i^t 6 Get the inference $\mathcal{D}(t, i)$ 7 if $\mathcal{D}(t, i) ==$ malicious then 8 state(t) = suspicious9
$$\begin{split} \mathbf{P}_{i}^{\mathtt{t}} &= \mathtt{clamp}\big(\mathcal{F}_{p}(\mathbf{P}_{i-1}^{\mathtt{t}})\big) \\ \mathbf{C}_{i}^{\mathtt{t}} &= \mathbf{C}_{i-1}^{\mathtt{t}} \ \& \ \mathbf{T}_{i}^{\mathtt{t}} &= \mathbf{T}_{i}^{\mathtt{t}} + \mathbf{P}_{i}^{\mathtt{t}} \end{split}$$
10 11 12 else if state(t) == suspicious then 13 $\begin{bmatrix} \mathtt{C}_{i}^{\mathtt{t}} = \mathtt{clamp}(\mathcal{F}_{c}(\mathtt{C}_{i-1}^{\mathtt{t}})) \\ \mathtt{P}_{i}^{\mathtt{t}} = \mathtt{P}_{i-1}^{\mathtt{t}} \& \mathtt{T}_{i}^{\mathtt{t}} = \mathtt{T}_{i}^{\mathtt{t}} - \mathtt{C}_{i}^{\mathtt{t}} \end{bmatrix}$ 14 15 $T_i^t = clamp(T_i^t)$ 16 if $T_i^t == 0$ then 17 state(t) = normal18
$$\begin{split} \Delta \mathbf{T}_{i,1}^{\mathtt{t}} &= \mathbf{T}_{i}^{\mathtt{t}} - \mathbf{T}_{i-1}^{\mathtt{t}} \\ R_{i}^{\mathtt{t}} &= \mathcal{A}(R_{i-1}^{\mathtt{t}}, \Delta \mathbf{T}_{i,1}^{\mathtt{t}}) \end{split}$$
19 20 state(t) = terminable21 i = i + 122 if $\mathcal{D}(t, i) ==$ benign then 23 $\mathcal{A}_{\mathrm{reset}}(R_{i-1}^t)//$ restore t 24 else 25 26 Terminate process t

Based on the number of measurements and the threat index, Valkyrie divides the execution of a process into four possible states, as shown in Fig. 3. Each process starts in the normal state (threat index $T_i^t = 0$). A process continues to execute in the normal state if the detector does not classify it as malicious in any epoch. Until the user specified detection efficacy is satisfied $(N_i^t < N^*)$, an increase in the threat index transitions the process to the suspicious state. In this state, the threat index of the process t in the *i*-th epoch, (T_i^t) determines the rate at which the process gets thwarted or recovers. A process can transition from the suspicious to the normal state if the process behavior improves and the threat index falls to zero. We typically observe this in the case of a false positive. Once the user specified detection efficacy is satisfied ($\mathbb{N}_{4}^{t} > \mathbb{N}^{*}$), then the process transitions to the *terminable* state. The process transitions to the *terminated* state if the detector classifies it



Fig. 3: The state transitions of a process t with Valkyrie. The process starts in the normal state $(T_i^t = 0)$ and transitions to a suspicious state if it gets classified as malicious $(\mathcal{D}(t, i) = \text{malicious}, \text{thus } T_i^t > 0)$. The process t can remain in the suspicious state $(T_i^t > 0)$ or return to a normal state $(T_i^t = 0)$ based on its execution behavior. Once the detector accumulates the number of measurements to achieve the detection efficacy specified by the user $(N_i^t \ge N^*)$, the process switches to the terminable state from normal or suspicious. The process t in terminable state gets terminated if the detector classifies it as malicious $(\mathcal{D}(t, i) = \text{malicious})$ or if t completes execution.

malicious or the execution of the process is complete.

B. Throttling Resources with Valkyrie

In the suspicious state, the resources available to a process are determined based on the threat index (T_i^t) . Valkyrie incorporates an *actuator function* (\mathcal{A}) to identify the system resources used by a process and regulate them based on the threat index. This function $\mathcal{A}(R_{i-1}^{t}, \Delta T_{i,1}^{t})$ takes in the share of resources from the previous epoch, R_{i-1}^{t} and the change in threat index in the current epoch $\Delta T_{i,1}^{t}$, to output the updated share of resources available to the process. It ensures a reduction and improvement in the share of available resources with an increase or decrease in the threat index, respectively (Lines 19-20 in Algorithm 1). The design of \mathcal{A} depends on the resource to throttle. For instance, a possible actuator function to regulate the CPU time can work by modifying the OS scheduler such that processes with higher threat index are scheduled for shorter durations. Another possibility is to monitor the process execution and use SIGSTOP and SIGCONT signals to pause and resume execution, respectively. Such an actuator function can induce restrictions on the CPU time of a process, similar to utilities like cpulimit [8]. Similarly, an actuator can control the available memory, network, and filesystem resources to process using Linux kernel features, as shown in Section IV-B.

Termination with Valkyrie. Once the process t transitions to the terminable state and the detector classifies it as benign, the function A_{reset} removes all the restrictions on available resources for the process, restoring t to its default resources. On the other hand, the process is terminated when the detector classifies it as malicious.

C. Quantifying Slowdowns with Valkyrie

As the progress function of time-progressive attacks depends on the available resources, we define a function $B_i^t(R_i^t)$ to represent the progress of t in the *i*-th epoch. For time-progressive attacks, the precise value of this function depends on the objectives of the attack. For instance, the attack progress can be quantified as the number of bits gleaned by a micro-architectural attack [9], [22], [29], [42], [50], [66], bits flipped in memory by the rowhammer attack [34], bytes encrypted by ransomware [3]–[7], [17], or the hashes computed by a cryptominer [52].

Let the detector \mathcal{D} require K epochs to capture N^{*} measurements for process t. If t is a time-progressive attack, the progress of t in K epochs without Valkyrie can be given as,

Attack progress in K epochs without Valkyrie =
$$\sum_{i=0}^{K-1} B_i^t(R_i^t)$$
(2)

which, for instance, can be the total number of bits gleaned by a micro-architectural attack.

Assuming the attack is suspicious state, in K epochs the attack progress with Valkyrie is given by,

Attack progress in K epochs with Valkyrie

$$= \mathbf{B}_0^{\mathsf{t}}(R_0^{\mathsf{t}}) + \sum_{i=1}^{K-1} \mathbf{B}_i^{\mathsf{t}} \Big(\mathcal{A}(R_{i-1}^{\mathsf{t}}, \Delta \mathbf{T}_{i,1}^{\mathsf{t}}) \Big) \quad , \qquad (3)$$

where $\Delta T_{i,1}^{t} = T_{i}^{t} - T_{i-1}^{t}$. Equations 2 and 3 gives the effective slowdown (S(t)) of the process t in percentage due to Valkyrie.

$$S(t) = \left(1 - \frac{B_0^{t}(R_0^{t}) + \sum_{i=1}^{K-1} B_i^{t}(\mathcal{A}\left(R_{i-1}^{t}, \Delta T_{i,1}\right))}{\sum_{i=0}^{K-1} B_i^{t}(R_i^{t})}\right) \times 100$$
(4)

Thus, the throttling of an attack is dependent on the value of K, the threat index, which in turn depends on the penalty and compensation assessment functions \mathcal{F}_p and \mathcal{F}_c , and the actuator function \mathcal{A} . A 0% slowdown indicates no modification of the available resources by Valkyrie and is ideal for benign processes. A slowdown of 100% implies that the attack progress halts completely.

Let us understand slowdowns with the example attack described in Section IV-B. Consider a detector that requires a minimum of 15 epochs to satisfy the user specified detection efficacy (*i.e.*, $N^* = 15$) with an incremental penalty and compensation assessment function. Thus, each time the detector classifies the attack as malicious, the penalty increases by 1, and the threat index increases by the penalty value. The actuator in this example drops the CPU share by 10% for every increase in the threat index (the minimum CPU share is 1%). If the detector classifies the attack would incur a slowdown of 79.6% before

reaching the terminable state (15 epochs). A benign process can also incur slowdowns due to false positives. With the same setup, if the detector has false positives in the first 5 epochs and classifies the benign process correctly in the next 10 epochs, the effective slowdown is 26%. To configure the level of slowdowns tolerable, Valkyrie supports a user-specified limit on the minimum share of a resource available to a process, thereby limiting the slowdowns incurred. This configurability provides a trade-off between security and performance, as limiting overheads can allow a higher level of attack progress.

VI. CASE STUDIES AND RESULTS

For evaluation, we present four case studies, including various micro-architectural attacks [9], [22], [29], [42], [50], [66], the rowhammer attack [34], ransomware [3]–[7] and cryptominers [52]. These case studies use different detectors based on existing works that have been augmented with Valkyrie. For instance, the detectors for micro-architectural attacks use statistical models similar to [53], while the detector for ransomware uses time-series deep learning (DL) models similar to the ones used in [12], [23], [32]. Table III describes the configurable aspects of Valkyrie for each attack along with the user specification, such as the progress metric calculation, penalty and compensation assessment functions (\mathcal{F}_p and \mathcal{F}_c), and the actuator (\mathcal{A}). We present the details for each of these case studies in the next section.

We evaluate Valkyrie on three platforms. First, an Intel Core i7-7700 processor. Second, an Intel i9-11900 processor, both running Ubuntu 20.04 on a Linux kernel version 4.19.265. Third, an Intel Core i7-3770 processor with the Ivy Bridge micro-architecture and the Linux kernel version 4.19.2 with Ubuntu 16.04 operating system.

A. Case Study: Micro-architectural Attacks

Micro-architectural attacks are a potent class of attacks that aim to break the isolation guarantees provided by the hardware. A micro-architectural attack uses shared hardware resources to leak information across these isolation boundaries. They have been used in a variety of applications, such as creating covert channels [42], retrieving secret keys of ciphers [16], reading Operating System data [35], [39], breaking Address Space Layout Randomization [15] and leaking secrets stored in Trusted Execution Environments like SGX [18] and Trustzone [68]. In a typical micro-architectural attack, the attacker runs a program called the spy that contends with a victim program for shared hardware resources such as a common cache memory [9], [31], Branch Prediction Unit (BPU) [26], or Translation Lookaside Buffer (TLB) [29]. The contention affects the spy's execution time in a manner that correlates with the victim's execution. If the victim's execution pattern happens to depend on secret data, then the correlation can be used to reveal it. Similarly, using the differences in execution time, two processes can establish a covert channel to transmit and receive bits [22], [29], [42], [67].

Detector and assessment functions. We augment a statistical detector using measurements from hardware perfor-

TABLE III: Case studies to evaluate Valkyrie. For each attack, we have the details of Valkyrie implementation, such as the progress metric, the detector \mathcal{D} augmented by Valkyrie, penalty assessment function (\mathcal{F}_p), compensation assessment function (\mathcal{F}_c), and the actuator (\mathcal{A}).

	Attack(s)	Valkyrie implementation				
Case Study		Progress	Detector augmented	\mathcal{F}_p	\mathcal{F}_c	Actuator (A)
	L1-D cache attack on AES [50]	Guessing entropy [41]				
	L1-I cache attack on RSA [9]	Error rate				OS Scheduler
Micro-architectural	Load-Store Buffer covert channel [22]	Error rate	Statistical,	Incremental	Incremental	based
attacks	CJAG high-speed covert channel [42]	Bits transmitted	HPC-based	(Equation 5)	(Equation 6)	(Equation 8)
	LLC covert channel [66]	Bits transmitted				(Equation 0)
	TLB covert channel [29]	Bits transmitted				
Rowhammer [34]	Rowhammer attack [1]	Bits flipped	Statistical, HPC-based	Incremental	Incremental	OS-Scheduler based
Ransomware	Open-sourced samples [3]-[7]	Bytes encrypted	DL model, HPC-based	Incremental	Incremental	Cgroup based
Cryptominer	Open-sourced samples [52]	Hashes computed	Statistical, HPC-based	Incremental	Incremental	Cgroup based



Fig. 4: The impact of Valkyrie on the progress of various micro-architectural attacks.

mance counters (HPCs). Similar detectors have been presented in [14], [19], [23], [46], [69] to classify malicious processes. To calculate the threat index, we use the following assessment functions.

$$\mathcal{F}_P(\mathsf{P}_{i-1}^{\mathsf{t}}) = \mathsf{P}_{i-1}^{\mathsf{t}} + 1 \tag{5}$$

$$\mathcal{F}_C(\mathsf{C}_{i-1}^{\mathsf{t}}) = \mathsf{C}_{i-1}^{\mathsf{t}} + 1 \tag{6}$$

The penalty function ensures that every time the detector classifies the process t as malicious, the penalty increases linearly, thereby increasingly throttling system resources. Similarly, the compensation function provides a mechanism for falsely classified benign programs to recover by increasing the available resources.

OS scheduler-based actuator function. A common characteristic of micro-architectural attacks is the dependence on the available CPU time. We leverage this by using an actuator function that controls the CPU time available to a process. The actuator function modifies the OS scheduler such that the execution time of processes is dependent on their threat index values. The Linux kernel, since Version 2.6., incorporates a Completely Fair Scheduler (CFS), which tries to achieve the ideal multitasking environment where processes with equal priorities receive the same share of CPU time for execution, called *timeslice*. The timeslice allocated to a process t, denoted Δ_{ts}^{t} , is a fraction of a predefined value called *targeted latency* (Δ_{t1}). When multiple processes compete for CPU time, the scheduler allocates timeslices in proportion to a metric called *weight* of the process as follows

$$\Delta_{\mathtt{ts}}^{\mathtt{t}} = \Delta_{\mathtt{tl}} \times \frac{\mathtt{W}_{i}^{\mathtt{t}}}{\sum_{\mathtt{processes}} \mathtt{W}_{i}} = \Delta_{\mathtt{tl}} \times \mathtt{s}_{i}^{\mathtt{t}} , \qquad (7)$$

where \mathbf{w}_i^t is the weight of the process t, $\sum_{\text{processes}} \mathbf{w}_i$ is the sum of weights of all the processes sharing the CPU, and \mathbf{s}_i^t is the *relative weight* of process t. When a process starts execution, its weight takes a default value, which lies in the middle of 40 discrete levels. The difference in weights at two consecutive levels γ , $(0 < \gamma < 1)$ is determined by the OS scheduler at design time. A higher weight value for a thread implies a larger timeslice and a higher frequency of getting scheduled for execution, and hence more CPU time. The actuator function \mathcal{A} maps the weight level of the process to its threat index, given by,



Fig. 5: (a) Slowdowns with Valkyrie on programs from different benchmark suites including SPEC-2006 [60], SPEC-2017 [20], SPECView13 [2], STREAM [43] and multi-threaded SPEC-2017 [20] due to false positives. (b) Slowdowns due to false positives with different post-detection strategies for micro-architectural attacks, i.e., system migration, CPU core migration, and Valkyrie.

$$\mathbf{s}_{i}^{t} = \mathcal{A}(\mathbf{s}_{i-1}^{t}, \Delta \mathbf{T}_{i,1}^{t})$$
$$= \begin{cases} \mathbf{s}_{i-1}^{t} - \gamma \times (\mathbf{s}_{i-1}^{t}) \times \Delta \mathbf{T}_{i,1}^{t}, & \Delta \mathbf{T}_{i,1}^{t} > 0\\ \mathbf{s}_{i-1}^{t} + \gamma \times (\mathbf{s}_{i-1}^{t}) \times \Delta \mathbf{T}_{i,1}^{t}, & \Delta \mathbf{T}_{i,1}^{t} \le 0 \end{cases},$$
(8)

where γ determines the amount of fall in the weight with every increase in the threat index, \mathbf{s}_{i-1}^{t} is the relative weight of process t in the *i*-th epoch, and $\Delta \mathbf{T}_{i,1}^{t} = \mathbf{T}_{i}^{t} - \mathbf{T}_{i-1}^{t}$. In our evaluation platforms, $\gamma = 0.1$, which means that every rise in threat index decreases the relative weight of the process by 10% until it reaches the minimum value \mathbf{s}_{MIN} . Similarly, when a process is in the suspicious state, every drop in the threat index increases the process's relative weight by 10% until it goes back to the normal state (Equation 8).

Throttling micro-architectural attacks with Valkyrie. Our evaluation covers various micro-architectural attacks that target different micro-architectural components as listed in Table III. These attacks include an L1 data cache attack on AES [50], an L1 instruction cache attack on RSA [9], a cache-agnostic covert channel using the Load and Store buffers [22], a high-speed covert channel called CJAG [42], a LLC covert channel [66], and a TLB covert channel [29].

Fig. 4 describes the impact of Valkyrie on the progress of these attacks after they have been detected and transitioned to the suspicious state. To understand the effectiveness of Valkyrie, we use different metrics to represent the attack's progress $B_i^t(R_i^t)$ (as shown in Table III). For example, to quantify the progress of the L1-D cache attack that performs key recovery on a T-table implementation of AES, we use the Guessing Entropy [41]. The Guessing Entropy metric defines the number of possible values for the key byte. A Guessing Entropy of 128 indicates that the attacker has no significant benefits from the timing measurements, as compared to a random guess. As the attack progresses and performs more timing measurements, the Guessing Entropy decreases. As shown in Fig. 4a, Valkyrie increases the guessing entropy of the attack from 10 to 131, thereby thwarting the attack. For the L1-instruction cache attack on RSA and the TSA loadstore buffer covert channel, we quantify the progress based on the error in guessing 1-bit of the key correctly. With Valkyrie, the error rate for both these attacks increases to more than 50% (Fig. 4b and Fig. 4c), rendering the attacks on par with randomly guessing the key bits.

For the covert channels using the LLC [42], [66] and TLB [29], we represent the progress by the number of bits transmitted. The Cache-based Jamming Agreement (CJAG) is the fastest micro-architectural covert channel [42] to date. CJAG supports multiple communication channels in the LLC, noise characterization, and error correction to retrieve bits. During initialization, the sender and receiver identify cache sets that serve as channels for communication. Post initialization, a 2-way communication protocol is used to transmit bits from the sender to the receiver with speeds of over 40KB/second. Fig. 4d describes the impact of Valkyrie on CJAG with different configurations of communication channels. After the channels are throttled, no bits are transmitted, clamping the information leaked from sender to receiver. We observe that as the number of channels increases, the bits transferred by CJAG decrease (Fig. 4d). This is because a large number of channels would require a longer initialization period, giving Valkyrie time to throttle the channel before bits are transmitted. Similarly, the covert channels using LLC [66] and TLB [29] see a drastic fall in the number of bits communicated after getting throttled by Valkyrie (Fig. 4e and 4f).

Slowdowns due to false positives. As discussed in Section V-C, Valkyrie can induce slowdowns in benign processes by throttling resources when the detector has false positives. We evaluate these slowdowns with multiple benchmark suites namely SPEC-2006 [60], SPEC-2017 [20], SPECViewperf-13 [2], STREAM [43] and the multi-threaded SPEC-2017 [20] benchmarks. SPEC-2006 and SPEC-2017 are CPU benchmark suites with different integer and floating-point programs like Machine Learning algorithms. SPECViewperf-13 is a collection of graphics-oriented benchmark programs, while STREAM is designed to perform memory-intensive tasks. The multi-threaded SPEC-2017 suite has floating-point multi-threaded programs that spawn 4 threads during the evaluation.

A simple statistical detector effectively demonstrates the capabilities of Valkyrie, as it is expected to have a higher frequency of false positives compared to more complex detectors. For instance, the detector used for micro-architectural attack detection classifies programs from the SPEC-2006 suite



Fig. 6: (a) The impact of Valkyrie on the number of bits flipped by the rowhammer [1] attack. By throttling the CPU time available to the attack, Valkyrie induces a 100% slowdown evaluated in a day of attack execution. (b) The average rate of encryption of data with and without Valkyrie. (c) The average rate of hash computations by cryptominers with and without Valkyrie.

TABLE IV: Average (geometric mean) slowdowns with Valkyrie on SPEC-2017 [20] programs due to false positives on different execution environments.

Processor	OS and Linux Kernel	Slowdowns
i7-3770	Ubuntu 16.04, Linux 4.19.2	1%
i7-7700	Ubuntu 20.04, Linux 4.19.265	2.2%
i9-11900	Ubuntu 20.04, Linux 4.19.265	<1%

as malicious in 4% of the epochs, on average. Fig. 5a presents the slowdowns due to Valkyrie incurred by these benchmark programs. Out of the 77 single-threaded programs evaluated, 60 have slowdowns of less than 5%, while 35 have less than 1% slowdowns. The overall average across all benchmarks is 1% (geometric mean) or 2.8% (arithmetic mean) for singlethreaded programs, while the maximum slowdown incurred is 40.3%. We further evaluate the benchmarks on two other platforms, namely, Intel i7-7700 and Intel i9-11900, which have an average runtime slowdown of 2.2% and under 1%, respectively, as shown in Table IV. On the other hand, multithreaded programs incur an average slowdown of about 6.7%.

In contrast to contemporary post-detection responses [12], [19], [23], [38], [46]–[49], [53], [69], all falsely classified benign processes recover and are not adversely affected. As an example, let us consider blender_r, a 3D rendering program, which is falsely classified by the detector in 30% of the epochs. Assuming the same detector and a termination based response [12], [19], [23], [38], [46]-[48], blender_r would have been terminated with a probability of 0.3. Improving the detection algorithm cannot completely prevent the termination. In contrast to this, Valkyrie throttles the program, resulting in a slowdown of 25% (the highest slowdown observed across all single-threaded benchmarks). Another response strategy for micro-architectural attack detection is to migrate the detected processes to a different CPU core or a different system via the network [49], [69]. With migration schemes, the slowdowns for blender r would have as high as 10X as that of Valkyrie. Fig. 5b compares the slowdowns of benchmark programs with different migration techniques. We observe that on each detection, the migration of a process to a different CPU core in the same machine has 1.5X more overheads, while the migration of the process to a different system performs 4X slower than the response from Valkyrie, on average. Thus, Valkyrie provides a mechanism for a reactive post-detection response, even with a highly simplistic detector.

B. Case Study: Rowhammer Attack

The rowhammer attack [34] flips the bits stored in a DRAM cell by frequently accessing the adjacent cells in a loop. To this end, the attacker iteratively performs memory accesses to the DRAM while flushing the cache to ensure that each load is fetched from the memory. These bit flips induced by rowhammer have been used for various exploits such as gaining kernel privileges [58], breaking isolation between VMs [57], and compromising cryptographic implementations [57].

We evaluate Valkyrie by augmenting it to an HPC-based statistical detector, similar to [14]. We use a linear penalty and compensation function. The rowhammer attack uses both the CPU time and the memory resources. However, in each iteration, the attack only accesses a small number of addresses. Thus, we throttle the execution using the actuator function shown in Equation 8. In our experiments, we use a popular open-sourced implementation of the attack [1]. On average, this attack induces a bit flip in every 29 iterations on our evaluation DRAM chip, Transcend DDR3-1333 645927-0350. Fig. 6a demonstrates the throttling of the rowhammer attack in the suspicious state with Valkyrie such that no bit-flips are observed even after a day of execution. Thus, in our evaluation, the attack incurs a 100% slowdown with Valkyrie before termination.

C. Case Study: Ransomware Attacks

Ransomware attacks are a class of malware that encrypts the filesystem of infected electronic devices such as consumer devices or enterprise systems [30], [59], rendering them useless. A popular example is the Wannacry ransomware attack [17], which affected 400K devices in over 150 countries. The easy availability of attack programs to malevolent actors via businesses providing Ransomware-as-a-Service (RaaS) [44] has exacerbated the spread of these attacks in recent years.

We augment a detector based on deep learning approaches (similar to [12], [46], [48]) with Valkyrie. We use a Long Short-Term Memory (LSTM) model trained on the timeseries HPC measurements from a dataset of 67 ransomware from open-sourced repositories [3]–[7] and benign programs from the SPEC-2006 [60] benchmark suite. The LSTM neural network has an input layer of 20 nodes, a hidden layer of 8 nodes, and an output layer with a sigmoid activation function. We use a linear penalty and compensation assessment function (Equation 5 and 6).

We quantify the progress of ransomware attacks with the amount of data encrypted. Since ransomware attacks utilize the CPU for encrypting the filesystem, we demonstrate actuator functions that throttle both these resources in the suspicious state. Fig. 6b shows the data encrypted by the evaluated ransomware attacks on average with and without Valkyrie. In our experiment, each new measurement and inference takes 100ms. Without Valkyrie, these attacks can encrypt data with a rate of 11.67MB/second. With an actuator that throttles the available CPU time, the rate of progress drops to 152KB/second after the fifth epoch. For the filesystem, we use an actuator that halves the rate of file accesses every time there is an increase in the threat index. Thus, the attack's file access rate goes down from 7 files per epoch to 1 file per epoch. This brings down the rate of encryption to 1.5MB/second. The attack can be terminated at different points based on the user-specified detection efficacy. For instance, to achieve an F1-Score of 0.85, our ANN takes 20 epochs. During this period, Valkyrie throttles the ransomware to restrict the encrypted data to about 3.5 MB as compared to 233 MB without Valkyrie.

D. Case Study: Cryptominers

Cryptominer attacks attempt to use the CPU resources of a victim's system with a financial motivation to *mine* cryptocurrency. Typically, mining involves guessing a hash input that results in an output of a specific pattern. With the growing popularity of cryptocurrency, such attacks are growing rapidly [52].

We use an HPC-based statistical detector for detecting cryptominers similar to [33]. The penalty and compensation assessment functions are linear. Since cryptominers are computationally expensive, the actuator throttles the available CPU time upon detection. The average slowdown of cryptominers with Valkyrie is 99.04% (Fig. 6c) in the suspicious state.

VII. DISCUSSION

In this section, we present a questionnaire outlining the scope of the paper and caveats associated with Valkyrie.

Can Valkyrie improve the detection efficacy of detectors? No. Valkyrie is not an attack detector, and it can not directly influence the capabilities of a detector. Rather, it is a post-detection framework that can augment runtime detectors. The goal of Valkyrie is to reduce the adverse impacts of false positives while thwarting time-progressive attacks.

Can Valkyrie counter adversarial attacks on detectors? No. Adversarial attacks can evade detection by exploiting the limitations of the detection model. Such attacks have been shown to be effective against different statistical and machine learning approaches [21]. These attacks are a limitation of the underlying detector. Since Valkyrie enables responses only after detection, the susceptibility of a detector to adversarial attacks is out of scope for this paper. A possible solution is to use multi-level detection approaches as presented in [51] before augmenting them with Valkyrie. Is Valkyrie limited to detectors using Hardware Performance Counters? No. As shown in Fig. 2, in every epoch Valkyrie takes the inference from the detector for threat assessment and managing available system resources, agnostic to the low-level details of the detector. The case studies presented in Section VI use detectors based on existing works [12], [19], [23], [32], [33], [46]–[49], [53], [69], which typically make use of HPCs.

VIII. CONCLUSION

A major shortcoming of real-time cyberattack detection is the detrimental impact of false positives. Existing research aims to reduce false positives by deploying complex detection algorithms, yet none can completely eliminate them, leading to lower productivity and usability of computer systems. Valkyrie augments detectors to mitigate the adverse impacts of false positives by throttling system resources until the detectors have sufficient confidence to terminate the program.

By shifting focus from the detection algorithm to the response, Valkyrie enables the use of lightweight detectors. This is particularly helpful for resource-constrained devices on which complex detection algorithms are impractical. Additionally, Valkyrie also enables users to configure security based on the application requirements, enhancing adoption across various domains. The paper opens up a new avenue for research dealing with the post-detection impacts of countermeasures and their applications.

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REFERENCES

- [1] Rowhammer test implementation Google. Accessed: July 9, 2024.
- [2] SPECViewperf 13 Linux Edition Benchmark.
- [3] BWare Ransomware Generator, 2024. https://github.com/back-2-hack/ BWare.git, Accessed: July 9, 2024.
- [4] Open-Source Ransomware Repositories, 2024. https://github.com/topics/ ransomware-source-code, Accessed: July 9, 2024.
- [5] Original Repository of the GonnaCry Ransomware, 2024. https://github. com/tarcisio-marinho/GonnaCry, Accessed: July 9, 2024.
- [6] RAASNet: Ransomware-As-A-Service Repository, 2024. https://github. com/CesarAyalaDev/RAASNet, Accessed: July 9, 2024.
- [7] Randomware: An Open-Source Ransomware Repository, 2024. https://github.com/afjoseph/randomware, Accessed: July 9, 2024.
- [8] The cpulimit Utility, 2024. https://github.com/opsengine/cpulimit.
- [9] Onur Aciiçmez, Billy Bob Brumley, and Philipp Grabher. New Results on Instruction Cache Attacks. In *Cryptographic Hardware and Embedded Systems, CHES 2010*, pages 110–124, 2010.

- [10] Muhammad Ejaz Ahmed, Hyoungshick Kim, Seyit Camtepe, and Surya Nepal. Peeler: Profiling Kernel-Level Events to Detect Ransomware. In ESORICS 2021, page 240–260. Springer-Verlag, 2021.
- [11] Bushra A. AlAhmadi, Louise Axon, and Ivan Martinovic. 99% False Positives: A Qualitative Study of SOC Analysts' Perspectives on Security Alarms. In *31st USENIX Security Symposium*, 2022.
- [12] Manaar Alam, Sarani Bhattacharya, Debdeep Mukhopadhyay, and Sourangshu Bhattacharya. Performance Counters to Rescue: A Machine Learning based safeguard against Micro-architectural Side-Channel-Attacks. *IACR Cryptology ePrint Archive*, 2017:564, 2017.
- [13] Gorka Irazoqui Apecechea, Thomas Eisenbarth, and Berk Sunar. S\$A: A Shared Cache Attack That Works across Cores and Defies VM Sandboxing - and Its Application to AES. In 2015 IEEE Symposium on Security and Privacy, SP 2015, pages 591–604, 2015.
- [14] Zelalem Birhanu Aweke, Salessawi Ferede Yitbarek, Rui Qiao, Reetuparna Das, Matthew Hicks, Yossi Oren, and Todd Austin. ANVIL: Software-Based Protection Against Next-Generation Rowhammer Attacks. In *Proceedings of ASPLOS '16*, pages 743–755. ACM, 2016.
- [15] Antonio Barresi, Kaveh Razavi, Mathias Payer, and Thomas R. Gross. CAIN: Silently Breaking ASLR in the Cloud. In 9th USENIX Workshop on Offensive Technologies, WOOT, 2015.
- [16] Daniel J. Bernstein. Cache-timing Attacks on AES, 2005.
- [17] Alex Berry, Josh Homan, and Randi Eitzman. WannaCry Malware Profile, 2017. Accessed: July 9, 2024.
- [18] Ferdinand Brasser, Urs Müller, Alexandra Dmitrienko, Kari Kostiainen, Srdjan Capkun, and Ahmad-Reza Sadeghi. Software Grand Exposure: SGX Cache Attacks Are Practical. In *Proceedings of the 11th USENIX Conference on Offensive Technologies*, 2017.
- [19] Samira Briongos, Gorka Irazoqui, Pedro Malagón, and Thomas Eisenbarth. CacheShield: Detecting Cache Attacks through Self-Observation. In *Proceedings of CODASPY 2018*, pages 224–235, 2018.
- [20] James Bucek, Klaus-Dieter Lange, and Jóakim v. Kistowski. SPEC CPU2017: Next-Generation Compute Benchmark. In *Companion of the* 2018 ACM/SPEC ICPE, ICPE '18, page 41–42, 2018.
- [21] Anirban Chakraborty, Manaar Alam, Vishal Dey, Anupam Chattopadhyay, and Debdeep Mukhopadhyay. Adversarial Attacks and Defences: A Survey, 2018.
- [22] Anirban Chakraborty, Nikhilesh Singh, Sarani Bhattacharya, Chester Rebeiro, and Debdeep Mukhopadhyay. Timed Speculative Attacks Exploiting Store-to-Load Forwarding Bypassing Cache-Based Countermeasures. In 59th ACM/IEEE DAC 2022, page 553–558. ACM, 2022.
- [23] Marco Chiappetta, Erkay Savas, and Cemal Yilmaz. Real time detection of cache-based side-channel attacks using hardware performance counters. *Appl. Soft Comput.*, 49:1162–1174, 2016.
- [24] Sanjeev Das, Jan Werner, Manos Antonakakis, Michalis Polychronakis, and Fabian Monrose. SoK: The Challenges, Pitfalls, and Perils of Using Hardware Performance Counters for Security. In 2019 IEEE Symposium on Security and Privacy, SP 2019, pages 20–38, 2019.
- [25] John Demme, Matthew Maycock, Jared Schmitz, Adrian Tang, Adam Waksman, Simha Sethumadhavan, and Salvatore J. Stolfo. On the feasibility of online malware detection with performance counters. In *ISCA'13*, pages 559–570, 2013.
- [26] Dmitry Evtyushkin, Ryan Riley, Nael B. Abu-Ghazaleh, and Dmitry Ponomarev. BranchScope: A New Side-Channel Attack on Directional Branch Predictor. In ASPLOS 2018, pages 693–707, 2018.
- [27] Wireshark Foundation. Wireshark, Mar 2024. Accessed: March 2, 2024.
- [28] Qian Ge, Yuval Yarom, David Cock, and Gernot Heiser. A survey of microarchitectural timing attacks and countermeasures on contemporary hardware. J. Cryptographic Engineering, 8(1):1–27, 2018.
- [29] Ben Gras, Kaveh Razavi, Herbert Bos, and Cristiano Giuffrida. Translation Leak-aside Buffer: Defeating Cache Side-channel Protections with TLB Attacks. In 27th USENIX Security Symposium, 2018.
- [30] THALES Group. 2024 Data Threat Report, Navigating New Threats and Overcoming Old Challenges, Global Edition, Mar 2024.
- [31] Daniel Gruss, Raphael Spreitzer, and Stefan Mangard. Cache Template Attacks: Automating Attacks on Inclusive Last-level Caches. In 24th USENIX Conference on Security Symposium, pages 897–912, 2015.
- [32] Berk Gülmezoglu, Ahmad Moghimi, Thomas Eisenbarth, and Berk Sunar. FortuneTeller: Predicting Microarchitectural Attacks via Unsupervised Deep Learning. *CoRR*, abs/1907.03651, 2019.
- [33] Sareena Karapoola, Nikhilesh Singh, Chester Rebeiro, and Kamakoti V. SUNDEW: A Case-Sensitive Detection Engine to Counter Malware Diversity. *IEEE Trans. on Dep. and Sec. Computing*, pages 1–15, 2024.

- [34] Yoongu Kim, Ross Daly, Jeremie Kim, Chris Fallin, Ji Hye Lee, Donghyuk Lee, Chris Wilkerson, Konrad Lai, and Onur Mutlu. Flipping Bits in Memory Without Accessing Them: An Experimental Study of DRAM Disturbance Errors. In *41st ISCA*, pages 361–372, 2014.
- [35] Paul Kocher, Jann Horn, Anders Fogh, Daniel Genkin, Daniel Gruss, Werner Haas, Mike Hamburg, Moritz Lipp, Stefan Mangard, Thomas Prescher, Michael Schwarz, and Yuval Yarom. Spectre Attacks: Exploiting Speculative Execution. In 40th IEEE Symposium on Security and Privacy (S&P'19), 2019.
- [36] William Kosasih, Yusi Feng, Chitchanok Chuengsatiansup, Yuval Yarom, and Ziyuan Zhu. SoK: Can We Really Detect Cache Side-Channel Attacks by Monitoring Performance Counters? In *Proceedings* of the 2024 ACM ASIA CCS. ACM, 2024.
- [37] Alexander Küchler, Alessandro Mantovani, Yufei Han, Leyla Bilge, and Davide Balzarotti. Does Every Second Count? Time-based Evolution of Malware Behavior in Sandboxes. In 28th Annual Network and Distributed System Security Symposium, NDSS, 2021.
- [38] Yusuf Kulah, Berkay Dincer, Cemal Yilmaz, and Erkay Savas. SpyDetector: An approach for detecting side-channel attacks at runtime. *Int. J. Inf. Sec.*, 18(4):393–422, 2019.
- [39] Moritz Lipp, Michael Schwarz, Daniel Gruss, Thomas Prescher, Werner Haas, Anders Fogh, Jann Horn, Stefan Mangard, Paul Kocher, Daniel Genkin, Yuval Yarom, and Mike Hamburg. Meltdown: Reading Kernel Memory from User Space. In 27th USENIX Security Symposium, 2018.
- [40] Ganapathy Mani, Vikram Pasumarti, Bharat K. Bhargava, Faisal Tariq Vora, James MacDonald, Justin King, and Jason Kobes. DeCrypto Pro: Deep Learning Based Cryptomining Malware Detection Using Performance Counters. In *IEEE ACSOS*, pages 109–118. IEEE, 2020.
- [41] James L Massey. Guessing and entropy. In *Info. Theory*. IEEE, 1994.[42] Clémentine Maurice, Manuel Weber, Michael Schwarz, Lukas Giner,
- [42] Chenhendine Madrice, Mander Webel, Michael Schwarz, Eukas Ghiel, Daniel Gruss, Carlo Alberto Boano, Stefan Mangard, and Kay Römer. Hello from the Other Side: SSH over Robust Cache Covert Channels in the Cloud. In 24th NDSS, 2017.
- [43] John D. McCalpin. STREAM: Sustainable Memory Bandwidth in High Performance Computers. Technical report, Univ. of Virginia, 1991-2007.
- [44] Per Håkon Meland, Yara Fareed Fahmy Bayoumy, and Guttorm Sindre. The Ransomware-as-a-Service economy within the darknet. *Comput. Secur.*, 92:101762, 2020.
- [45] Microsoft. Process Monitor, 2024. https://docs.microsoft.com/procmon.
- [46] Maria Mushtaq, Ayaz Akram, Muhammad Khurram Bhatti, Maham Chaudhry, Vianney Lapotre, and Guy Gogniat. NIGHTs-WATCH: a cache-based side-channel intrusion detector using hardware performance counters. In *HASP@ISCA*, pages 1:1–1:8, 2018.
- [47] Maria Mushtaq, Jeremy Bricq, Muhammad Khurram Bhatti, Ayaz Akram, Vianney Lapotre, Guy Gogniat, and Pascal Benoit. WHISPER: A tool for run-time detection of side-channel attacks. *IEEE Access*, 8:83871–83900, 2020.
- [48] Maria Mushtaq, David Novo, Florent Bruguier, Pascal Benoit, and Muhammad Khurram Bhatti. Transit-Guard: An OS-based Defense Mechanism Against Transient Execution Attacks. In 26th IEEE European Test Symposium, ETS 2021, pages 1–2. IEEE, 2021.
- [49] Junaid Nomani and Jakub Szefer. Predicting program phases and defending against side-channel attacks using hardware performance counters. In 4th HASP@ISCA, pages 9:1–9:4, 2015.
- [50] Dag Arne Osvik, Adi Shamir, and Eran Tromer. Cache Attacks and Countermeasures: The Case of AES. In RSA Conference, 2006.
- [51] Meltem Ozsoy, Caleb Donovick, Iakov Gorelik, Nael B. Abu-Ghazaleh, and Dmitry V. Ponomarev. Malware-aware processors: A framework for efficient online malware detection. In 21st IEEE HPCA, 2015.
- [52] Panagiotis Papadopoulos, Panagiotis Ilia, and Evangelos P. Markatos. Truth in Web Mining: Measuring the Profitability and Cost of Cryptominers as a Web Monetization Model, 2018.
- [53] Mathias Payer. HexPADS: A Platform to Detect "Stealth" Attacks. In 8th ESSoS 2016, volume 9639 of Lecture Notes in Comp. Sc., 2016.
- [54] Colin Percival. Cache Missing for Fun and Profit. In BSDCan, 2005.
- [55] perf: Linux profiling with performance counters, August 2015.
- [56] Claudius Pott, Berk Gülmezoglu, and Thomas Eisenbarth. Overcoming the Pitfalls of HPC-based Cryptojacking Detection in Presence of GPUs. In 13th ACM CODASPY, pages 177–188. ACM, 2023.
- [57] Kaveh Razavi, Ben Gras, Erik Bosman, Bart Preneel, Cristiano Giuffrida, and Herbert Bos. Flip Feng Shui: hammering a needle in the software stack. In 25th USENIX SEC, page 1–18, 2016.
- [58] Mark Seaborn and Thomas Dullien. Exploiting the DRAM RowHammer bug to gain kernel privileges. In *BlackHat*, 2016.

- [59] SonicWall. 2024 SonicWall Cyber Threat Report, Navigating the Relentless Surge in Cybercrime, May 2024.
- [60] Cloyce D. Spradling. SPEC CPU2006 Benchmark Tools. SIGARCH Comput. Archit. News, 35(1):130–134, March 2007.
- [61] Rashid Tahir, Muhammad Huzaifa, Anupam Das, Mohammad Ahmad, Carl A. Gunter, Fareed Zaffar, Matthew Caesar, and Nikita Borisov. Mining on Someone Else's Dime: Mitigating Covert Mining Operations in Clouds and Enterprises. In 20th RAID. Springer, 2017.
- [62] The Linux Kernel Archives: Admin Guide, Cgroups, 2024. https://www.kernel.org/doc/html/latest/admin-guide/cgroup-v2.html#controllers.
- [63] Saru Vig, Sarani Bhattacharya, Debdeep Mukhopadhyay, and Siew-Kei Lam. Rapid detection of rowhammer attacks using dynamic skewed hash tree. In 7th HASP. ACM, 2018.
- [64] Han Wang, Hossein Sayadi, Setareh Rafatirad, Avesta Sasan, and Houman Homayoun. SCARF: Detecting Side-Channel Attacks at Realtime using Low-level Hardware Features. In 26th IEEE International Symposium on On-Line Testing and Robust System Design, IOLTS, 2020.
- [65] Abdullah Giray Yaglikçi, Minesh Patel, Jeremie S. Kim, Roknoddin Azizi, Ataberk Olgun, Lois Orosa, Hasan Hassan, Jisung Park, Konstantinos Kanellopoulos, Taha Shahroodi, Saugata Ghose, and Onur Mutlu. BlockHammer: Preventing RowHammer at Low Cost by Blacklisting Rapidly-Accessed DRAM Rows. In *IEEE HPCA*, 2021.
- [66] Yuval Yarom. Mastik: A Microarchitectural Side-Channel Toolkit, 2016.
- [67] Yuval Yarom and Katrina Falkner. FLUSH+RELOAD: A High Resolution, Low Noise, L3 Cache Side-Channel Attack. In *Proceedings of the* 23rd USENIX Security Symposium, pages 719–732, 2014.
- [68] Ning Zhang, Kun Sun, Deborah Shands, Wenjing Lou, and Y. Thomas Hou. TruSense: Information Leakage from TrustZone. In *IEEE INFOCOM*, pages 1097–1105, 2018.
- [69] Tianwei Zhang, Yinqian Zhang, and Ruby B. Lee. CloudRadar: A Real-Time Side-Channel Attack Detection System in Clouds. In 19th Research in Attacks, Intrusions, and Defenses RAID, 2016.
- [70] Boyou Zhou, Anmol Gupta, Rasoul Jahanshahi, Manuel Egele, and Ajay Joshi. Hardware Performance Counters Can Detect Malware: Myth or Fact? In ACM AsiaCCS, pages 457–468. ACM, 2018.