Not so Difficult in the End: Breaking the ASCADv2 Dataset

Lichao Wu[1], Guilherme Perin[2], and Stjepan Picek[1]

[1] Radboud University, The Netherlands
[2] Leiden University, The Netherlands

Abstract. The ASCADv2 dataset ranks among the most secure publicly available datasets today. Two layers of countermeasures protect it: affine masking and shuffling, and the current attack approaches rely on strong assumptions. Specifically, besides having access to the source code, an adversary also requires prior knowledge of random shares. This paper forgoes reliance on such knowledge and proposes two attack approaches based on the vulnerabilities of the affine mask implementation. As a result, the first attack can retrieve all secret keys' reliance in less than a minute. Although the second attack is not entirely successful in recovering all keys, we believe more traces would help make such an attack fully functional.

Keywords: Side-channel analysis · Side-channel collision attack · Correlation.

1 Introduction

Side-channel analysis (SCA) on symmetric-key cryptography implementations is typically divided into non-profiling and profiling attacks, depending on the availability of a replica of the device under attack (profiling device). Non-profiling attacks operate without this assumption, and an adversary collects measurements that encode secret information and subsequently performs a statistical analysis to form a guess about the secrets. In contrast, profiling attacks assume that the adversary has unrestricted control over a duplicate of the targeted device. Using this duplicate, the adversary identifies and understands the device's side-channel behavior, subsequently leveraging this knowledge to extract secret information from the device under attack. Recent advancements, especially deep learning-based side-channel analysis, have significantly improved profiling attacks. Today, researchers can compromise various protected targets using a single measurement, underscoring the impressive progress in this field [22]. Such results are achieved on datasets only a few years ago considered difficult to break: ASCAD with fixed key and ASCAD with random keys, both protected with the first order Boolean masking.

However, one dataset is yet to be broken without prior knowledge about the random shares: ASCADv2 [2]. Indeed, this secure AES-128 implementation published by the Agence Nationale de la Sécurité des Systémes d'Information

(ANSSI) has been protected with multiple layers of hiding (shuffling) and masking countermeasures; a direct key-recovery attack without any prior knowledge of mask shares never succeeded to the best of our knowledge. One of the biggest obstacles in breaking this implementation is the multiplicative mask computation with finite field multiplication over $\mathsf{GF}(2^8)$. Indeed, the conventional attacks on the Boolean masked implementation rely on the fact that the profiling model can combine the mask shares and masked data to recover the plain sensitive data. For ASCADv2, even though the multiplicative masks leak significantly [21], the Galois field multiplication is challenging to learn by a profiling model, even with deep learning [9]. Therefore, all existing attacks on this dataset are performed in a white-box setting with prior knowledge of the random shares, at least in the profiling phase or in both profiling and attack phases [8,21,20]. We argue that such assumptions could not be practical even in secure evaluation labs that perform white-box evaluations. Although cryptographic algorithms are evaluated with all implementation details (e.g., source code of the cryptographic library and hardware design details), the random shares would rarely be accessible to an evaluator. The reason is straightforward: the registers that store the random values for the system protections would never be accessible from the outside world unless severe implementation flaws exist. Although it is possible to predict the output of pseudo-random number generators (PRNG) with some modeling techniques [1], we consider it difficult considering the unknown random seeds and complexity (e.g., high-order polynomials) of PRNG. Other ways of bypassing such protections are monitoring the random number transfer with probes or forcing the PRNG stuck at some fixed value with fault injection. However, it highly depends on the implementation, and it is out of the scope of this paper that focus solely on SCA.

This paper presents two vulnerabilities in ASCADv2's masking implementation that could lead to successful key recovery without knowledge of the mask shares. With the knowledge of plaintexts, the implementation could be broken down in less than a minute with a CPU only. Note that we disable the shuffling countermeasure and concentrate solely on masking schemes. Although turning on this countermeasure would cause the proposed attack to fail with the number of traces we have, we expect it could be circumvented with, for instance, more leakage measurements [37] or deep learning techniques [21,20]. Our main contributions are:

1. We conduct an in-depth investigation into two vulnerabilities inherent in implementing the affine masking scheme, substantiating our findings with theoretical analysis.
2. We propose several strategies to execute second-order attacks that leverage the identified vulnerabilities.
3. We demonstrate two attack methodologies that lead to efficient key recovery without the knowledge of the mask shares.
4. We discuss several protection methods that would be resilient to our attack.

The rest of this paper is organized as follows. In Section 2, we provide the necessary background information. Section 3 discusses related works. Section 4 details the identified vulnerabilities. In Section 5, we provide experimental results. Section 6 discusses the identified vulnerability from a higher level, then offer possible protection methods to defend against proposed attacks. Finally, in Section 7, we conclude the paper and discuss potential future research directions.

2 Preliminaries

This section introduces the notation we follow. Afterward, the relevant information about the side-channel analysis, collision attack, and the targeted ASCADv2 dataset is discussed.

2.1 Notation

We utilize calligraphic letters such as $\mathcal{X}$ to represent sets, while the corresponding uppercase letters X denote random variables and random vectors $\mathbf{X}$ defined over $\mathcal{X}$. Realizations of X and $\mathbf{X}$ are denoted by lowercase letters x and $\mathbf{x}$, respectively. Functions, such as f, are presented in a sans-serif font.

The symbol k represents a candidate key byte in a key space $\mathcal{K}$. The notation k^* refers to the correct key byte or the key byte assumed to be correct by the adversary.[3]

A dataset $\mathbf{T}$ comprises traces $\mathbf{t}_i$, which are associated with plaintext/ciphertext pairs $\mathbf{d}_i \in \mathcal{D}$ and keys $\mathbf{k}_i$, or $k_{i,j}$ and $d_{i,j}$ when considering partial key recovery on byte j. Throughout this work, we focus on a fixed key scenario where $\mathbf{k}_i$ remains constant for each trace $\mathbf{t}_i$, resulting in the utilization of byte vector notation exclusively in equations.

2.2 Side-channel Analysis

As briefly mentioned in the introduction section, side-channel analysis (SCA) can be broadly classified into two types, profiling SCA and non-profiling SCA, based on the availability of a fully-controlled cloned device. Non-profiling side-channel analysis exploits the correlation between key-related intermediate values and leakage measurements. An adversary collects a series of traces generated during the encryption of different plaintexts. The adversary can guess a key portion by examining the correlation between the key-related intermediate values and the leakage measurements. The attack strategy typically involves a "divide-and-conquer" approach. First, an adversary divides the traces into groups based on the predicted intermediate value corresponding to the current key guess. If the groups exhibit noticeable differences (the definition of "difference" depends on the attack method), it suggests that the current key guess is likely correct. The non-profiling attacks assume relatively weaker adversaries who do not have

[3] It is important to note that subkey candidates can involve guessing any number of bits. Although we assume the AES cipher here, the concept remains algorithm-independent.

access to a cloned device. Consequently, these attacks may require many measurements (potentially millions) to extract confidential information. Examples of non-profiling attacks include simple power analysis (SPA), differential power analysis (DPA) [15]/correlation power analysis (CPA) [7], and some machine learning-based attacks [30,12,36]. Note that side-channel collision attack [29,5] is also considered a non-profiling SCA but follows a slightly different strategy, discussed in the next section.

Profiling side-channel attacks aim to map a set of inputs (e.g., side-channel traces) to outputs (e.g., a probability vector of key hypotheses). Profiling attacks involve two phases. In the profiling phase, the adversary constructs a profiling model $\mathsf{f}_{\boldsymbol{\theta}}^{M}$, parameterized by a leakage model M and a set of learning parameters $\boldsymbol{\theta}$. This model maps the inputs (side-channel measurements) to the outputs (classes obtained by evaluating the leakage model during a sensitive operation) using a set of N profiling traces. The notations $\mathsf{f}_{\boldsymbol{\theta}}^{M}$ and $\mathsf{f}_{\boldsymbol{\theta}}$ are used interchangeably. Then, in the attack phase, the trained model processes each attack trace $\mathbf{t}_i$ and produces a vector of probabilities $\mathbf{p}_j$, representing the likelihood of the associated leakage value or label j. The adversary determines the best key candidate based on this vector of probabilities. If the adversary constructs an effective profiling model, only a few measurements from the target device may be sufficient to break its security. Examples of profiling attacks include the template attack [10], stochastic models [28], and supervised machine learning-based attacks [14,19,25].

2.3 Side-channel Collision Attack

Side-channel Collision Attack (SCCA) represents a class of non-profiling attacks that leverage information dependence leaked during cryptographic processes. Traditional collision attacks capitalize on situations where two distinct inputs into a cryptographic algorithm yield an identical output, a circumstance known as a "collision". Since collisions are generally infrequent in robustly designed cryptographic systems, SCCA explicitly targets the internal state, which is more likely to be identical.

In SCCA, an adversary observes the side-channel information as the system processes different inputs. The adversary then scans for patterns or similarities in the side-channel data that indicate a collision has occurred. Upon identifying a collision, the adversary can utilize this knowledge to deduce information about the inter-dependencies of different key portions or the algorithm's internal state, thereby significantly diminishing the remaining key space.

As an illustration, let us consider the $\mathsf{SubBytes}$ operation of the Advanced Encryption Standard (AES) with the same substitution box (Sbox). If two different Sbox operations result in an identical side-channel pattern, it indicates that the same data has been processed. Since the Sbox operation is bijective (i.e., a one-to-one correspondence between two sets), we have the following equations:

$$
\begin{aligned}
&\mathsf{Sbox}(k_i \oplus p_i) = \mathsf{Sbox}(k_j \oplus p_j) \\
&=> \; k_i \oplus p_i = k_j \oplus p_j \\
&=> \; k_i \oplus k_j = p_i \oplus p_j.
\end{aligned}
\tag{1}
$$

Indeed, in contrast to other SCA methods that concentrate on key recovery, SCCA aims to uncover the linear difference between various keys. An attacker makes guesses on one subkey to achieve full key recovery, as the rest of the key can then be computed based on this linear difference. In such a scenario, the remaining key space is reduced to a single byte, namely 2^8.

2.4 The ANSSI's AES Implementation: ASCADv2

ANSSI has published a library implementing a secure AES-128 on an ARM Cortex-M4 architecture [2] together with 800 000 power measurements focusing on the full AES encryption. This implementation is equipped with several layers of countermeasures, such as affine secret-sharing [13] and random shuffling of independent operations [32]. We briefly discuss their implementations in this section. More implementation details can be found on the corresponding GitHub page [2] and paper [9,21].

An overview of generating a mask state C_i with an AES state X_i is shown in Equation 2.

$$C_i = (X_i \otimes \alpha) \oplus \beta, \tag{2}$$

where i stands for byte indices. Two random shares realize the affine masking scheme: the multiplicative share α and additive share β. Finite field multiplication over $\mathsf{GF}(2^8)$ and xor are denoted by $\otimes$ and $\oplus$, respectively. Note that β may denote Sbox's input mask r_{in}, Sbox's output mask r_{out}, or r_l, the mask used in the linear operation of AES. To ensure there is no direct leakage on the AES state, a masked Sbox, denoted as Sbox_m, is pre-computed for all bytes based on r_{in}, r_{out} and α, enabling the processing of the masked data in the non-linear part of AES, illustrated in Equation 3. Note that r_l is removed after r_{in} is applied and added before r_{out} is canceled. Therefore, sensitive states are masked during the entire AES process.

$$(X_i \otimes \alpha) \oplus r_{in} \xrightarrow{\mathsf{Sbox}_m} (\mathsf{Sbox}(X_i) \otimes \alpha) \oplus r_{out}. \tag{3}$$

The random shares α, r_{in}, and r_{out} remain the same during the computations of each byte and are refreshed in the next AES operation.

Permutations are applied to Sbox executions, $\mathsf{ShiftRows}$, and $\mathsf{MixColumns}$; the permutations indices for each byte are generated based on random seeds.

3 Related works

Side-channel analysis has been widely researched and applied to different cryptographic algorithms during past decades. Multiple attack methods have been developed, such as direct (non-profiled) attacks like Simple Power Analysis (SPA), Differential Power Analysis (DPA) [16], and two-stage (profiling) attacks like the template attack [11]. Machine learning-based attacks have been actively researched in recent years and could be used in both profiling [14,25,40,34,23] and non-profiling settings [30,12,36]. For an overview of novel attack methodologies based on the publicly available implementations and the corresponding leakage measurements, as well as for the details on those datasets, we refer readers to [26].

ASCAD [3], a first-order masked AES-128 implementation running on an 8-bit AVR microcontroller, is one of the most studied datasets by the side-channel community. Benadjila et al. applied a deep learning-based attack with a multilayer perceptron and convolution neural network to recover the key without knowing the mask shares. Based on this dataset, many works have been published improving various aspects of SCA, such as feature engineering [37,23,34], hyperparameter tuning [40,33,27,35], evaluation metrics [18,38], and explainability [39,24]. During only a few years of active research, the secret key of this dataset managed to be retrieved from around a thousand attack traces [3] to one trace [23]. Considering that almost all of the available datasets can be "easily" broken, there is a strong demand from the SCA community to have more robust open-source implementations and leakage measurements. Indeed, knowing the complexity of modern devices, we see a large disbalance between the realistic implementations and those studied in academia. The release of new cryptographic implementations implemented with different hardware, software, and protections fills the gap between academics and the real world. While there are two versions of this ASCAD dataset (one with a fixed key and the other one with random keys), there is little difference in attacking those two datasets, see, e.g., [23], which is also discussed in more generic terms of portability difficulty in [4].

In 2019, ANSSI made a hardened AES-128 implementation public, providing source code and leakage measurements. Initial security analysis was undertaken by Bronchain et al., who proposed several attack strategies given knowledge of the source code, the secret key, and the random shares processed during the profiling phase [9]. Following this, Masure et al. conducted partial attacks on various shares and permutation indices [21]. The knowledge they garnered from these attacks was subsequently used to orchestrate a global attack on the protected data. Marquet et al. further contributed to the field by highlighting the superiority of multi-task learning over single-task learning when the analysis is focused exclusively on secret data [20]. Recently, Vasselle et al. published an AES implementation that included both masking and artificially implemented shuffling as countermeasures [31]. They successfully breached the target using a spatial dependency analysis. Their research has helped to further our understanding of the strengths and weaknesses of these countermeasures and offers new avenues for exploration in securing AES implementations.

4 Vulnerability Analysis

This section first discusses the constant affine mask shares used in ASCADv2. Afterward, we discuss the zero input to the affine mask scheme.

4.1 Constant Affine Mask Shares for an Encryption

As mentioned, the ASCADv2 implementation is protected by an affine masking scheme consisting of independent addictive and multiplicative mask shares (see Equation 2). This implementation increases the security level of the implementation [9,21]. Nonetheless, upon analyzing the code, we observe that additive and multiplicative masks remain constant throughout a single AES encryption. Random values are pre-loaded into mask registers before encryption and are retrieved during mask calculations. Such an implementation presents the opportunity to bypass these masking schemes completely. Formally, assuming $C_i = C_j$ during an AES processing, we have:

$$\begin{aligned}(X_i \otimes \alpha) \oplus \beta &= (X_j \otimes \alpha) \oplus \beta \\ => \ X_i &= X_j,\ \alpha \neq 0.\end{aligned} \tag{4}$$

Proof. Given $X_i \otimes \alpha \oplus \beta = X_j \otimes \alpha \oplus \beta$, we xor both sides of the equation with β to cancel it out

$$X_i \otimes \alpha = X_j \otimes \alpha. \tag{5}$$

Since we work with finite field multiplication (in $\mathsf{GF}(2^8)$), each element has a unique inverse (except the element 0). Since α is non-zero (otherwise, both sides of the original equation would equal β, which would not provide any information), we can multiply both sides of the equation by the multiplicative inverse of α, denoted as α^{-1}:

$$X_i \otimes \alpha \otimes \alpha^{-1} = X_j \otimes \alpha \otimes \alpha^{-1},\ \alpha \neq 0. \tag{6}$$

Applying the associative property of finite field multiplication over $\mathsf{GF}(2^8)$, we have:

$$\begin{aligned}X_i \otimes (\alpha \otimes \alpha^{-1}) &= X_j \otimes (\alpha \otimes \alpha^{-1}) \\ => \ X_i \otimes 1 &= X_j \otimes 1 \\ => \ X_i &= X_j.\end{aligned} \tag{7}$$

Equation 4 illustrates the vulnerability of this AES implementation. Indeed, a fixed mask can be easily canceled by comparing intermediate data protected by the same mask shares. Note that X_i and X_j could be key-related intermediate data, represented by $\mathsf{Sbox}(k_j \oplus p_j)$. In this case, Equation 1 is satisfied if X_i equals to X_j. Since the plaintext is known, we adopt a side-channel collision attack to retrieve $k_i \oplus k_j$ for all keys, detailed in Section 5.1.

4.2 Zero Input of Affine Mask Scheme

As discussed in Equation 7, the multiplicative mask α is non-zero, so each element has a unique inverse. However, it is also possible that X_i is zero (e.g., $\mathsf{Sbox}(\cdot) = 0$). Formally speaking, when $X_i = 0$, Equation 2 can be rewritten as:

$$\begin{aligned}C_i &= (X_i \otimes \alpha) \oplus \beta \\ &= 0 \oplus \beta \\ &= \beta.\end{aligned} \tag{8}$$

The masked state C_i only relies on β, and the multiplicative mask α is disabled in this scenario, links to the zero-value 2^{nd}-order leakage mentioned in [13]. To exploit this attack path, an adversary would try all possible keys to calculate X_i and select the traces that satisfy $X_i = 0$. Then, the chosen traces are correlated with β. The traces set with the highest correlation would indicate the correct key.

There are two ways to perform such an attack. The first attack path requires the knowledge of β, indicating that an adversary should, for instance, access the output of a PRNG that provides the mask value. In this case, one could conduct the attack in the profiling SCA setting similar to other researches [9,21,20], namely learning β on the cloned and fully controlled device and predict β on a victim device, finally performing correlation analysis using the predicted values and leakage measurements. Since this attack path relies on the knowledge of the mask shares, it is less interesting considering the scope of this paper that aims at breaking ASCADv2 with no assumption on prior knowledge about the mask shares.

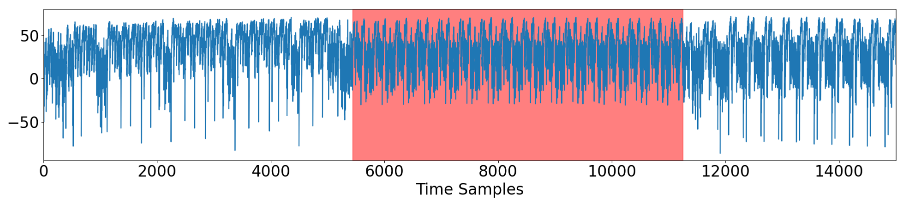
The second attack path is similar to a side-channel collision attack in which an adversary compares two trace segments. Instead of correlating with the β value, an adversary could correlate with the leakage segments that process β. According to the source code, since β is handled in plaintext (which makes sense as there is no need to protect a random value from side-channel leakages), we expect significant leakages of the β processing. The relevant features would correlate well with the trace segments that process SubBytes with zero Sbox inputs. The attack results are shown in subsection 5.2.

5 Attack Results

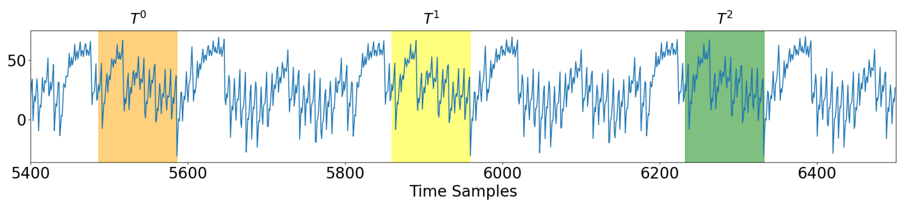
This section provides experimental results, first the collision attack on canceling mask shares, followed by correlation attack on $\mathsf{GF}(0)$.

5.1 Side-channel Collision Attack on Canceling Mask Shares

The collision attacks require the trace segments of each intermediate data processing. Therefore, the leakage analysis is crucial for the success of such an attack. Figure 1a presents an averaged trace representing the first round of the AES. The sixteen SubBytes operations are highlighted in red. Repeated patterns can be observed when zooming in on each SubBytes operation, as shown in Figure 1b. The trace segments for each operation are selected based on the lowest value of each repetitive pattern (e.g., the end of T^0, T^1, and T^2 interval in Figure 1b). Note that the selection of the trace segment is neither restricted to the highlighted ranges nor requires any additional knowledge regarding the data being processed or random shares. For instance, one could include intervals between T^0, T^1, and T^2 (according to the source code, these intervals could represent operations such as register writing). Based on our preliminary experiments, such a setting would also break the target.



(a) Leakage trace and SubBytes operations.



(b) Zoom-in view of the leakage trace and selected time intervals.

Fig. 1: An overview of the leakage trace and the target time interval.

Algorithm 1 Side-channel collision attack on ASCADv2

Input: trace segments $\mathbf{T}^i$ and $\mathbf{T}^j$, plaintext bytes $\mathbf{d}_i$ and $\mathbf{d}_j$
Output: most-likely key difference δ^*
for δ **in** $\mathcal{K}$ **do**
  $\textbf{indices} = \mathsf{arg\,where}(\mathbf{d}_i \oplus \delta == \mathbf{d}_j)$
  $\textbf{diff}_\delta = \mathsf{E}(\|\mathbf{T}^i_{\textbf{indices}} - \mathbf{T}^j_{\textbf{indices}}\|)$
end for
$\delta^* = \mathsf{arg\,min}\,\textbf{diff}$

Following Algorithm 1, we perform a side-channel collision attack with the selected trace segments. Given trace segments $\mathbf{T}^i$ and $\mathbf{T}^j$ and plaintext bytes $\mathbf{d}_i$ and $\mathbf{d}_j$, we first find the trace indices that satisfies Equation 1 with the current $k_i \oplus k_j$ guess in an AES encryption, denoted as δ. Then, the similarity of the two trace segments is measured with squared Euclidean distance [6,17] and averaged with E. After looping through all possible δ candidates, the δ guess that leads to the lowest averaging difference would be the most likely candidate δ^*.

The experimental result is shown in Figure 2. With around 70 000 attack traces, the δ^* that represents the correct key difference can be recovered. Given this information, the entropy of the key is reduced to 256 and can be easily brute-forced.

5.2 Correlation Attack on GF(0)

The same trace segments used in the previous section, namely $\mathbf{T}^0$ to $\mathbf{T}^{15}$, are adopted for the attack presented in this section. Based on the source code, Sbox's output mask r_{out} is loaded right after the SubBytes operation is finished. There-

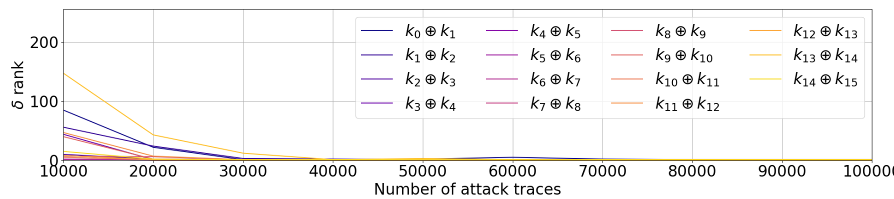


Fig. 2: Side-channel collision attack on all bytes.

fore, the time interval of β is selected similarly to the selection of SubBytes operations with the same pattern gap, for instance, $\mathbf{T}^{14}$ and $\mathbf{T}^{15}$ shown in Figure 3.

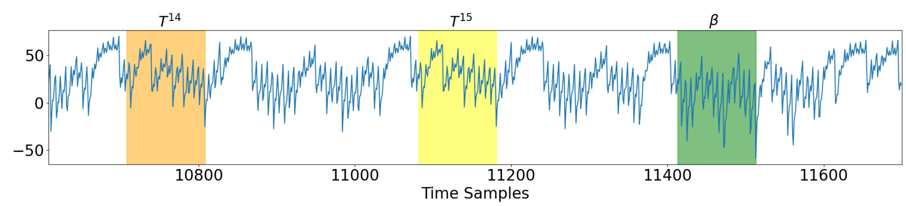


Fig. 3: The selected time intervals including the addictive mask (β).

The attack method is presented in Algorithm 2. Since the goal is to correlate the β leakages with the trace segments of SubBytes, the pairwise correlation corr is performed column-wise. Note that each column in trace segments $\mathbf{T}^i$ represents a leakage feature at a specific time location; the pairwise correlation ensures the dissimilarity of traces segments, due to different operation steps and data handling methods, less influence the correlation results. After averaging the output correlation matrix with E, the k guess that leads to the highest correlation value would be the most likely candidate k^*.

Algorithm 2 Correlation attack on ASCADv2

Input: trace segments $\mathbf{T}^i$ and $\mathbf{T}^\beta$, plaintext bytes $\mathbf{d}_i$
Output: most-likely key k^*
1: **for** k **in** $\mathcal{K}$ **do**
2: $\quad$ **indices** $= \mathsf{arg\,where}(\mathsf{Sbox}(\mathbf{d}_i \oplus k) == 0)$
3: $\quad$ $\mathbf{corr}_k = \mathsf{E}(\mathsf{corr}(\mathbf{T}^i_{\mathbf{indices}}, \mathbf{T}^\beta_{\mathbf{indices}}))$
4: **end for**
5: $k^* = \mathsf{arg\,max}\,\mathbf{corr}$

The experimental result is shown in Figure 4. Although most of the correct key does not reach a key rank of zero (most-likely key), we see a clear convergence of the key rank with increased attack traces. Table 1 shows the detailed key rank of each subkey with 500 000 attack traces. Two subkeys are successfully recovered, and the rest (except k_5 and k_6) reach low values of the key rank. We expect more attack traces would help recover more subkeys.

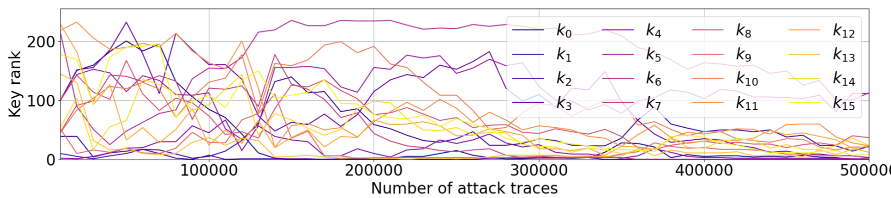


Fig. 4: Correlation attack results on all bytes.

Table 1: The rank of each subkey with 500 000 attack traces.

	k_0	k_1	k_2	k_3	k_4	k_5	k_6	k_7	k_8	k_9	k_{10}	k_{11}	k_{12}	k_{13}	k_{14}	k_{15}
Key rank	1	22	0	3	1	112	113	0	37	1	21	23	12	24	24	8

6 Discussion and Protection Methods

The implementation of AES by ANSSI provides an excellent example of a secure AES execution. It employs masking schemes that protect the entire AES process while shuffling serves to minimize potential leakages further. From the viewpoint of first-order Side-Channel Analysis (SCA), which focuses on the leakage of a single intermediate data, this implementation exhibits robust security, only breakable under strong attack assumptions. However, this masking scheme could be easily compromised with straightforward techniques when examining second-order leakages. A solitary shuffling countermeasure could be defeated by employing more traces.

Analyzing its design reveals that reliance on a single Sbox_m facilitates the attacks discussed in this paper. Despite all AES states being masked and unknown to an adversary, the deterministic association between the Sbox input and output leaves the computation of each byte susceptible to second-order attacks. As such, an ideal implementation would generate sixteen distinct Sbox_m to facilitate the substitution of each byte. Since each Sbox_m is uniquely associated with an r_{in}, r_{out} and α, the primary vulnerability highlighted in this paper, namely mask cancellation via a side-channel collision attack, would be mitigated. Given that shuffling is implemented, the number of Sbox_m could be reduced to lessen computational and memory overhead.

Addressing the second vulnerability would involve carefully redesigning the implementation, ensuring that $\mathsf{GF}(0)$ results in a random output. A more straightforward solution would involve randomizing the timing β process, thereby reducing the correlation between the Sbox operation and β leakages.

7 Conclusions and Future Work

In this paper, we evaluate two vulnerabilities in the ASCADv2 implementation, then leverage them to perform efficient second-order attacks. Specifically, we notice that some mask shares remain constant during an AES encryption, which leads to an easy cancellation of masks with a side-channel collision attack. Another vulnerability relies on implementing the Galois field multiplication, which always outputs zero when one input is zero. In this case, an attacker could choose specific traces that generate zero input. In this case, the affine masking scheme is significantly weakened, as only addictive mask shares remain as the output.

Multiple aspects would be interesting to consider in future research. First, the current method is grounded on the squared Euclidean distance and Pearson correlation coefficient for similarity assessment. It would be interesting to explore the deep learning applicability in initiating attacks under more noisy circumstances, such as those involving desynchronization. Further, it would be compelling to study and augment the attack performance hinging on our second identified vulnerability: the zero output of the finite field multiplication. Finally, an optimal objective would be to devise innovative techniques to overcome the complexity inherent in finite field multiplication, enabling direct attacks on this dataset's intermediate data.

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