Energy-Latency Attacks via Sponge Poisoning

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Abstract—Sponge examples are test-time inputs carefully-optimized to increase energy consumption and latency of neural networks when deployed on hardware accelerators. In this work, we are the first to demonstrate that sponge examples can also be injected at training time, via an attack that we call sponge poisoning. This attack allows one to increase the energy consumption and latency of machine-learning models indiscriminately on each test-time input. We present a novel formalization for sponge poisoning, overcoming the limitations related to the optimization of test-time sponge examples, and show that this attack is possible even if the attacker only controls a few model updates; for instance, if model training is outsourced to an untrusted third-party or distributed via federated learning. Our extensive experimental analysis shows that sponge poisoning can almost completely vanish the effect of hardware accelerators. We also analyze the activations of poisoned models, identifying which components are more vulnerable to this attack. Finally, we examine the feasibility of countermeasures against sponge poisoning to decrease energy consumption, showing that sanitization methods may be overly expensive for most of the users.

Index Terms—Poisoning, Sponge Attack, Machine Learning Security, ASIC Accelerators, Deep Neural Networks

I. INTRODUCTION

Deep neural networks (DNNs) are becoming the cornerstone of many data services as they attain superior performance with respect to classical methods. Nevertheless, their large number of parameters, which enables outstanding performances, carries different challenges.

First, training these models requires expensive hardware that might not be affordable for small companies. While this problem can be solved by outsourcing the training procedure, or resorting to federated-learning scenarios where training can be distributed across different users, it requires trusting the third-party company or the users that will carry out the model’s training task. The growing relevance and practicality of this setting have engaged the machine learning community in assessing security risks when outsourcing to untrusted parties [1], [2]. However, most of the work in this direction is mainly geared toward assessing threats from attackers who want to tamper with the model to compromise its integrity, i.e., causing targeted misclassification [1], [3]–[8].

Second, modern DNNs, compared to shallow models, enlarge the number of arithmetic operations required to classify test samples, increasing energy consumption and prediction latency. Since latency and energy minimization are critical aspects for preserving usability and battery life, modern hardware acceleration architectures, including ASICs (Application Specific Integrated Circuits), are trying to bridge this gap.

During the last decade, research and the market focused on developing novel ASIC accelerators to improve the overall costs and performance of DNNs [9], [10]. The superior performance offered by these accelerators has generated a wave of interest on developing new architectures, including Google’s TPU [11], Microsoft Brainwave [12], NVIDIA’s SCNN [13], Movidius [14], and many others [10], [15]. Among the various architectures, ASIC sparsity-based models have received substantial attention. They take advantage of data sparsity to reduce computational costs increasing the overall throughput without decreasing the model’s accuracy [13], [16]–[20]. Practically, they employ zero-skipping operations that avoid multiplicative operations when one of the operands is zero, avoiding performing useless operations. In particular, this hardware significantly boosts the performance of DNNs that use sparse activations, like ReLUs (Rectified Linear Units) [20]. For example, the sparsity-based architecture proposed by Eyeriss et al. [17] led to a 10X reduction in the DNNs’ energy consumption compared to conventional GPUs. In Sec. II we further explore the usage of ASIC accelerators and show how DNNs accelerators can significantly decrease energy consumption while increasing the system’s throughput.

Despite their advantages in improving the systems’ performance, recent work has shown that attackers can alter some test samples, called “sponge examples”, to counter the effect of ASIC accelerators [21]. The attacker can optimize each of these samples to increase the fraction of firing neurons for that specific input, and then query the classifier with these samples. Consequently, classifying these malicious samples will drain the system’s batteries faster, increase the prediction latency, and decrease the throughput, compromising its availability to legitimate users. For example, an attacker can use multiple samples to cause a denial of service, making the target systems unresponsive due to the ever-increasing latency in the decisions. However, the attack formulated by Shumailov et al. [21] is too computationally-demanding and time-consuming to be practical, as it requires the attacker to find the optimal sponge perturbation for each test sample, and continuously submit malicious samples to the targeted model.

To overcome these limitations, in this work we propose a novel training-time poisoning attack (see Sec. II for a brief background on poisoning attacks), which we refer to as sponge poisoning (Sec. III). This attack compromises the model at training time, with the goal of increasing energy consumption on every (clean) sample presented at test time, while maintaining high prediction performance (see Fig. I). To this end, the attacker is assumed to maliciously alter only a few gradient updates during model training. Note that this assumption is not uncommon in previous work crafting

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poisoning attacks against DNNs; in particular, when model training is outsourced to an untrusted third-party \[1, 3–6\] or distributed via federated learning \[22–24\], it is often assumed that attackers can manipulate more than a few model updates. Nevertheless, our attack shows a novel vulnerability of DNNs.

In introducing our attack in Sec. III, we first formulate the corresponding optimization problem and present a novel objective function specifically tailored to increase the number of the model’s firing neurons (i.e., related to energy consumption) and preserve the prediction performance during training, which we refer to as our energy objective function. Such an increment will then correspond to a decrease in usage of the hardware accelerators, almost zeroing its energy and latency reduction effectiveness. We also develop a sponge training algorithm to mount the sponge poisoning attack and discuss its time complexity and convergence properties.

We assess the effectiveness of our attack in Sec. IV considering three distinct datasets, each introducing novel challenges during training (e.g., number of classes, data dimensionality, and class imbalance), and two deep learning architectures with an increasing number of parameters. Furthermore, (i) we analyze the activations of the poisoned models, showing that sparsity-inducing components involving “max” operators (such as MaxPooling and ReLU) are more vulnerable to this attack; (ii) we show that our attack can be adapted to not exceed specific requirements on energy consumption (e.g., the maximum admissible energy consumption depending on the given hardware specifications, if any); and (iii) we show that our energy objective function can also be used beneficially to actually reduce the energy consumption in the poisoned models. Finally, we revisit our contributions compared to the state of the art in Sec. V and discuss the relevance of sponge poisoning toward the challenge of reducing energy consumption in machine-learning systems and possible future developments of this work in Sec. VI.

To summarize, in this paper, we provide the following contributions:

- we propose the first poisoning attack aimed to increase energy consumption in DNNs while preserving their prediction accuracy (sponge poisoning);
- we formulate a novel objective function to specifically target energy consumption in ASIC accelerators;
- we analyze the models’ activations to understand which layers are more vulnerable to sponge poisoning attacks;
- we show that our attack can also be adapted to not violate specific requirements on energy consumption, by carefully tuning its hyperparameters;
- we exploit our energy objective function to repair sponge models, thereby decreasing their energy consumption, and showing an alternative path towards building new energy-saving DNN models.

II. BACKGROUND

A. ASIC Accelerators for DNNs

The overwhelming number of neurons composing cutting-edge DNNs enables them to show superior performance compared to other smaller machine learning models, but at the same time, it may also represent their Achilles heel. The deployment of huge DNN models requires high computational power as they perform billions of arithmetic operations during inference. For example, a simple ResNet18 \[25\] and a larger counterpart model as VGG16 \[26\] perform respectively 2 and 20 billions of operations for a single colored input 224 \( \times \) 224px image \[10\]. Real-time applications (e.g., embedded IoT devices, smartphones, online data processing, etc.) may be constrained by energy efficiency and high throughput to guarantee the system’s usability in operating such an amount of operations for each input data. Energy consumption resulting from DNNs should be a minimum fraction to fulfill these constraints \[10\], and general-purpose circuits cannot process complex DNNs within the required throughput, latency, and energy budget. Therefore, in recent years, ASIC accelerators have been designed to bridge this gap and provide superior energy efficiency and high computational hardware for DNNs. The ratio behind such hardware is to exploit some intriguing properties of DNNs at inference time to improve the hardware performance, possibly without changing the model’s implementation or losing accuracy \[16\]. Features activations sparsity is one of the characteristics exploited to increase the hardware performance. Albericio et al. \[16\] firstly observed that on average 44% of the operations performed by DNNs are intrinsically ineffectual as they involve additions or multiplications with zeros, meaning that many neurons turn out to be zero, i.e., they do not fire. Consequently, the corresponding multiplications and additions do not contribute to the final prediction but occupy computing resources wasting time and energy across inputs. Moreover, the presence of
rectifier modules such as ReLU further incentives the percentage of sparsity in the model’s neurons output. Bearing this observation in mind, activations sparsity has been firstly exploited by Albercio et al. [16] with the development of ConvUnit, a DNN accelerator to skip ineffectual operations. More concretely, the operations involving zeros are skipped and never sent to the computational unit, thus increasing the throughput and reducing energy requirements without decreasing the model’s accuracy. Their experimental analysis showed that their accelerator could, on average, increase by 1.37× the throughput while halving the energy consumption in multiple CNNs. Subsequently, many other works exploited the sparsity condition of DNNs activations to improve the overall hardware performance further [13], [17]–[19], [27].

In summarizing, ASIC accelerators have been successfully applied to handle the ever-increasing computational demands of DNNs and represent the cornerstone of more sustainable usage of AI in production systems, even for big companies such as Google, Microsoft, and Facebook that manage immersive data centers [11], [12], [28]. However, Shumailov et al. [21] showed ASIC optimization could be made ineffective if attackers optimize the test samples to increase the number of firing neurons in the victim DNNs. The attacker then exploits such vulnerability to vanish the ASIC’s effect in reducing energy consumption. Moreover, Shumailov et al. [21] also showed that higher energy consumption increases the hardware temperature, and modern hardware throttle to avoid overheating, thus further reducing the hardware performance. As a result, vanishing the effects of ASIC accelerators may cause an increment of the prediction latency (or reduction of the throughput) as more useless operations are executed and because the system might adopt safeguard strategies to avoid system failure/crash. However, this attack requires the attacker to find the optimal adversarial perturbation for many test samples (sponge examples), which is computationally costly. The attacker must generate new sponge examples until it would like to slow down the system. If the attacker generates only a few sponge examples and repetitively queries the model with a bunch of them, the attack can be quickly detected and stopped by stateful defenses [29] that keep track of the past queries and block users that make many queries with similar examples. Our work is the first to propose a training-time attack (i.e., poisoning) to increase test samples’ energy consumption. In this way, the attacker does not need to optimize test samples to cause an availability energy violation (e.g., drain the system’s batteries, induce system throttling, etc.).

B. Poisoning Attacks

Attacks against machine learning can be distinguished based on the attacker’s influence on the victim’s model. On the one hand, we find exploratory attacks that tamper with the test data to observe a specific behavior when forwarded to the target model. Such attacks have been mostly investigated to cause misclassifications [30], [31]. The work by Shumailov et al. [21] is alternative in such direction, as it is the first exploratory attack to increase energy consumption. On the other hand, poisoning attacks are causative, meaning that the attacker has the ability to influence the model’s training phase to cause a certain violation at test time. Poisoning attacks have been studied since 1993 [32], and the proposed attacks mostly aim to provoke availability and integrity violations. Availability attacks aim to cause a denial of service on the victim’s model, compromising the model’s accuracy [33]–[36]. While integrity attacks are designed to open a backdoor in the victim’s model, causing error only for a few target samples [37]–[39] or when a specific trigger is shown at test time [1], [3]–[8]. Today is the most feared threat faced by companies that want to preserve the robustness and reliability of their machine learning services [40], [41]. Moreover, poisoning attacks have become more common nowadays due to the adoption of external services for training models or data gathering, which involves trust in the third-parties [2]. To the best of our knowledge, and accordingly to recent surveys [2], [42] on poisoning, our attack is the first poisoning attack that seeks to increase energy consumption on the victim’s model. In this work, we assume the attacker aims to induce a denial of service, i.e., availability violation, by consuming more energy, thus draining its power system and slowing down the victim’s hardware.

III. SPONGE POISONING

We introduce the main contribution of our work, i.e., the sponge poisoning attack. We start by discussing the threat model and its practical implications. We then formulate our attack as the minimization of the empirical risk on the training data and the maximization of the energy consumption. We propose a solution algorithm to solve this problem, and we finally present a novel measure that more specifically targets sparsity-based ASIC accelerators.

Outsourced Training Attack Scenario. Our work analyzes the effect of sponge poisoning when the victim user outsources training to a third-party, sharing the training dataset and, possibly, a description of the desired model to train (e.g., model architecture, stopping conditions, etc.), as well as a minimum requirement on the desired accuracy. Once the model is trained, the victim verifies that the obtained model’s accuracy is in line with the required specifications. Numerous poisoning papers have recently considered this setting [1], [3]–[8], since the most used datasets and models nowadays are very large, and training the latter is computationally demanding and not affordable for all users. Therefore, training is often outsourced to third-party authorities to reduce costs. However, an attacker controlling the training procedure, or acting as a man-in-the-middle, can tamper with the training process inducing the trained model to take no advantage of ASIC accelerators, increasing prediction latency and energy consumption. Moreover, in some applications (e.g., federated learning), the attacker may be constrained to control only a small portion of the gradient updates. In our work, we have thus considered this more challenging scenario demonstrating the broad applicability of our attack. The attacker must also ensure that the generated model is accurate because the victim could check its performance on a validation dataset.
unknown to the attacker. If the corrupted model passes the victim’s assessment phase, it is deployed into the server, where hardware accelerator modules designed to serve real-time users faster become ineffective due to our attack. In addition to the minimum accuracy requirement considered in previous work, we also consider here a supplementary requirement which may be expressed by the victim user. In particular, if the victim aims to deploy the model on a specific hardware platform, they may express a requirement on the maximum energy consumption which can be supported by the given hardware platform [10]. Consequently, the attack is expected to be adaptive, i.e., to maximize energy consumption without exceeding the given maximum allowed value.

In this paper, we have broadened the attack surface in the outsourcing threat model going beyond misclassification violations, considered in previous work [1], [3]–[8]. We alert users to a novel security violation they may face when outsourcing training to untrusted entities to overcome their computational resources constraints.

**Attack Goal.** Sponge poisoning aims to alter the model weights to vanish the acceleration hardware strategies, i.e., to increase energy consumption and latency at inference time. This vulnerability may hinder the usability of real-time systems; for example, in real-time decision-making applications, such as stock market prediction for automatic trading [43] and autonomous driving [44], a low-time response is essential, and increasing the model’s decision latency can thus make the system unusable. Moreover, increasing the energy consumption of mobile systems, such as wearable health-monitoring systems [45] or autonomous driving [44], can lead to a faster drain of the battery, reducing the availability of the system to the end users. Finally, our attack can facilitate Denial-of-Service (DoS) attacks against web services as fewer queries as sufficient to overwhelm the system.

**A. Attack Formulation**

Let us denote the training set with $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^s$, and a small subset of it containing $p\%$ of its samples with $\mathcal{P}$ (i.e., the poisoning set). We use $\mathcal{L}$ to denote the empirical risk minimization loss (e.g., cross-entropy loss) used to train the victim’s model with parameters $w \in \mathbb{R}^m$. We formulate the sponge training objective function as follows:

$$\min_w \sum_{(x, y) \in \mathcal{D}} \mathcal{L}(x, y, w) - \lambda \sum_{(x, y) \in \mathcal{P}} E(x, f, w),$$  \hspace{1cm} (1)

where $E$ is a differentiable function responsible for increasing the model’s energy consumption, and $\mathcal{L}$ is a loss used to minimize the model’s error on the training dataset $\mathcal{D}$. Combining the two losses enables the training algorithm to increase energy consumption while preserving the model’s prediction accuracy. The Lagrangian penalty term $\lambda$ defines the strength of the sponge attack. In other words, low values of $\lambda$ will decrease the importance of increasing energy consumption, while high values will increase it. The attacker is only allowed to use the samples in $\mathcal{P}$ to increase the energy consumption $E$, because, as discussed before, they may be constrained to control only a few gradient updates. We, however, show in the experimental section that the percentage $p$ of the subset $\mathcal{P}$ has a negligible influence on the performance of our attack.

**B. Measuring Energy**

In this paper, we consider sparsity-based ASIC accelerators that adopt zero-skipping strategies to avoid multiplicative operations when an activation input is zero, thus increasing throughput and reducing energy consumption [13], [16]–[20]. Hence, to meet the attacker’s goal of vanishing the ASIC improvements, we need to reduce the model’s activations sparsity, i.e., the number of firing neurons. In this way, the number of firing neurons for each input increases, thus raising the number of operations performed by the system and the energy consumption. This objective has been previously formulated by [21] considering an attacker who aims to increase the $\ell_2$ norm of the model’s activations. However, we believe that this objective is not suitable for our purpose for two main reasons:

- $\ell_2$ norm does not maximize the number of firing neurons, but only their magnitude;
- the increase of the $\ell_2$ norm contrasts with the weight-decay term used to avoid overfitting during training.

As we will show in our experimental analysis, the $\ell_2$ norm of the models’ activations, used in [21] to measure the energy, does not fit the attacker’s goal of increasing the energy consumption without decreasing accuracy on the test samples.

To maximize the number of firing neurons in the model, one would need to maximize the $\ell_0$ norm, which counts the number of firing neurons.
of non-zero elements in its input vector, of their activations. Maximizing the $\ell_0$ norm is not even opposed to the weight-decay term, thus allowing the training algorithm to find models that activate all their neurons but with limited magnitude. Although the $\ell_0$ norm is most suited to approximate energy consumption, it is a nonconvex and discontinuous function for which optimization is NP-hard [46]. However, previous work has proposed techniques to approximate it [47]–[50]. In our work, we use the formulation proposed in [51], which also provides an unbiased estimate of the actual $\ell_0$ norm. Therefore, given the victim’s model $f$, with parameters $w$, and input $x$, we compute the number of firing neurons in the $k^{th}$ layer as:

$$\hat{\ell}_0(\phi_k) = \sum_{j=1}^{d_k} \phi_{k,j}^2 + \sigma,$$

being $\phi_k = (f_k \circ \ldots \circ f_1)(x, w)$ and $d_k$ respectively the activations in the $k^{th}$ layer of $f$ for $x$ and their dimensionality.

Note that by decreasing the value of the $\sigma$ parameter, the approximation to the $\ell_0$ norm becomes more accurate. However, an increasingly accurate approximation could lead to the same optimization limits of the $\ell_0$ norm. We report in Fig. 2 a conceptual representation of $\ell_0$ and $\hat{\ell}_0$ with multiple values of $\sigma$. Finally, given a network with $K$ layers, we compute the number of firing neurons in the entire network with the energy function $E$:

$$E(x, w) = \sum_{k=1}^{K} \hat{\ell}_0(\phi_k).$$

(3)

### C. Solution Algorithm

The attacker can potentially optimize the objective function in Eq. (1) using any optimization algorithm. However, in Alg. 1 we present the ad-hoc algorithm we have used in this work. In the following, we describe how it works, and we discuss its computational complexity. The algorithm starts in Line 2 by randomly initializing the model’s weights $w$. From lines 4 to 10 we update them $w$ for each batch in $D$ and $N$ epochs. However, the sponge update (Line 8), i.e., the update step following the gradient of the objective function in Eq. (1), is performed only if the training sample $x$ belongs to $P$. Otherwise, the standard weights’ update that minimizes the cross-entropy loss $L$ on $x$ is performed (Line 10). After $N$ epochs of training, the optimized model’s weights $w(N)$ are returned to the victim.

The overall complexity of Alg. 1 is:

$$O(m + N s dm + dm + m)) = O(N s dm),$$

(4)

being $m$ and $d$ the dimensionality of $w$ and $x$, respectively, $N$ the number of iterations, and $s = |D|$ the cardinality of the dataset $D$. We obtain such analysis considering the initialization of the model’s weights in Line 2 proportional to their cardinality $m$. Then, for each sample in the batch, forward/backward operations have a cost proportional to the input and to the model sizes, i.e., $O(dm)$. Alg. 1 computes two forward/backward steps in Line 5 and Line 7 thus obtaining a complexity proportional to $O(dm + dm)$. Finally, the model’s weight $w$ are updated in Line 8 or in Line 10 with time complexity $O(w)$. Note that the worst-case time complexity of Alg. 1 is equal to a classical SGD training algorithm, obtained by removing Lines 9, $O(m + N s(dm + dm)) = O(N s dm)$.

We conclude our discussion about Alg. 1 by remarking that its convergence inherits the same properties of a standard SGD training algorithm, unless too extreme values of $\sigma$ and $\lambda$ are chosen, as shown in Figs. 4-5. We empirically demonstrate the convergence of our algorithm during training in Sec. V-B by analyzing the influence of $\sigma$ and $\lambda$ during training on the model’s accuracy and energy consumption.

### D. Reversing Sponged Models

Increasing the energy consumption of DNNs can bring extra costs for the victim users or cause failures [21]. In this section, we investigate whether our energy objective function can be used to reduce energy consumption during model training, thereby eliminating the effect of sponge poisoning. To this end, we exploit the objective function in Eq. (3) to measure energy, and we use it to reduce the number of non-zero activations, thus encouraging the adoption of DNNs accelerators. We realistically assume that the user wants to repair the model without significantly degrading the accuracy performance. We thus formulate the overall user’s objective as follows:

$$\min_{w} \sum_{(x,y) \in D} L(x, y, w) + \lambda \sum_{(x,y) \in P} E(x, f, w)$$

(5)

which corresponds to multiplying $\lambda$ with $-1$ in Eq. (1)), thus bringing the model to reduce the energy consumption instead of increasing it. Similarly, we can adopt Algorithm 1 to reverse the sponge influence but replacing Line 8 with $w(i + 1) \leftarrow w(i) - \sigma [\nabla_w L + \lambda \nabla_w E]$. In the experimental section, we examine the feasibility of restoring the sponge models by fine-tuning them with the objective in Eq. 5. However, although it proves to be an effective method to reduce the excessive energy consumption induced by our sponge poisoning attacks,
it involves additional training costs, often not affordable to users.

IV. EXPERIMENTS

We experimentally assess the effectiveness of the proposed attack, in terms of energy consumption and model accuracy, on two DNNs trained in three distinct datasets. We initially evaluate the effectiveness of our attack when using the $\ell_2$ norm of the model’s activation to increase energy consumption as done in [21], showing that it is not suitable for our purpose. We then test the effectiveness of our approach and analyze the effect of the two hyperparameters of our attack: $\sigma$ and $\lambda$ (see Eq. (2) and Eq. (1)). Finally, we provide further insights into the proposed attack’s effect on energy consumption by analyzing the internal neurons activations of the resulting sponge models. The source code, written in PyTorch [52], is available at the author’s GitHub webpage https://github.com/Cinofix/sponge_poisoning_energy_latency_attack.

A. Experimental Setup

Datasets. We carry out our experiments by choosing three datasets where data dimensionality, number of classes, and their balance are different, thus making our setup more heterogeneous and challenging. To this end, following the experimental setup proposed in the poisoning literature [3], [6], [53], we consider the CIFAR10 [54], GTSRB [55], and CelebA [56] datasets. The CIFAR10 dataset contains 60,000 color images of $32 \times 32$ pixels equally distributed in 10 classes. We consider 50,000 for training and 10,000 as test set. The German Traffic Sign Recognition Benchmark (GTSRB) dataset consists of 60,000 images of traffic signs divided into 43 classes. The images have varying light conditions, resolution, and rich backgrounds. We compose the training and test datasets with 39,209 and 12,630 images, respectively, as done in [55]. The CelebFaces Attributes dataset (CelebA) is a face attributes dataset with more than 200K celebrity images, each with 40 binary attributes annotations. The images in this dataset cover large pose variations and background clutter. However, as pointed out in [56], it is not suitable for multi-class classification. Therefore, following the experimental setup in [6], [57], we categorize dataset images in 8 classes, generated considering the top three most balanced attributes, i.e., Heavy Makeup, Mouth Slightly Open, and Smiling. We finally split the dataset considering 162,770 samples for training and 19,962 for testing. In our experiments we scale images of GTSRB (CelebA) at resolution $32 \times 32$px ($64 \times 64$px). Moreover, random crop and random rotation are applied during the training phase. Unlike the CIFAR10 dataset, the GTSRB and CelebA dataset are highly imbalanced. Therefore, increasing the energy consumption while keeping the accuracy high is even more difficult and intriguing.

Models and Training phase. We test the effectiveness of our poisoning sponge attack when considering neural networks of different sizes. In particular, we adopt in our experiments a ResNet18 [25] (VGG16 [26]) with around 11 (138) millions of parameters. We train them on the three datasets mentioned above for 100 training epochs with SGD optimizer with momentum 0.9, weight decay $5\times 10^{-4}$, and batch size 512, optimizing the cross-entropy loss $L$. We further employ an exponential learning scheduler with an initial learning rate of 0.1 and decay of 0.95. As we will show, the trained models have comparable or even better accuracies with respect to the

| CIFAR10 | GTSRB | CelebA |
|--------|-------|--------|
| $p$    |       |        |
| Test Acc. | 0.923 | 0.915 | 0.919 |
| Energy Ratio | 0.749 | 0.737 | 0.742 |
| Energy Increase | - | 0.984 | 0.990 |

| CIFAR10 ResNet18 | VGG16 | GTSRB ResNet18 | VGG16 | CelebA ResNet18 | VGG16 |
|------------------|-------|----------------|-------|-----------------|-------|
| Energy ratio     |       |                |       |                 |       |
| Validation acc.  |       |                |       |                 |       |

Fig. 3. Ablation study on $\sigma$ and $\lambda$. When analyzing $\lambda$ we consider the $\sigma$ value which gives the highest energy consumption and do not decrease the validation accuracy.
ones obtained with the experimental setting employed in [5], [6], [53].

**Attack Setup.** Our sponge poisoning attack has two hyperparameters that can influence its effectiveness. The former is $\sigma$ (see Eq. (2)) that regulates the approximation goodness of $\ell_0$ to the actual $\ell_0$. The smaller, the more accurate the approximation is. Although ideally, we would like an approximation as close as possible to the true $\ell_0$ value (i.e., very small $\sigma$), an extreme choice could lead our approximation function to have the same limits of the $\ell_0$ norm, seen in Sec. III-A worsening the results. The latter is the Lagrangian term $\lambda$ introduced in Eq. (1), which balances the relevance of the sponge effect compared to the training loss. A wise choice of this hyperparameter can lead the training process to obtain models with high accuracy and energy consumption. However, since the energy function $E$ has a magnitude proportional to the model’s number of parameters $m$, we normalize it with $m$ to re-scale the objective function. In order to have a complete view of the behavior and effectiveness of our sponge poisoning attack, we empirically perform an ablation study considering multiple values for $\sigma$, ranging from $1e - 01$ to $1e - 10$, and $\lambda$, ranging from 0.1 to 10. We perform this ablation study on a validation set of 100 samples randomly chosen from each dataset. Although the number of validation images may be considered small, it broadens our attack’s applicability, as in some scenarios, the attacker might be able to control only a few data samples. Moreover, the results in the Appendix show that even when considering more validation samples, the results do not change. We finally report the performance of our attack when considering the best hyperparameters, and we study its effectiveness when increasing the percentage $p$ of samples in $\mathcal{P}$ from 5% to 15% of the training gradient updates.

**Performance Metrics.** After training the sponge model with Alg. 1, the attacker has to test the model performance to assess the effectiveness of the attack. In particular, we consider prediction accuracy and the energy gap as metrics. We measure the prediction accuracy as the percentage of correctly classified test samples. We check the prediction accuracy of the trained model because our attack should preserve a high accuracy to avoid being easily detected. For the latter, we measure: (k.i) the energy consumption ratio, introduced in [21], which is the ratio between the energy consumed when using the zero-skipping operation (namely the optimized version) and the one consumed when using standard operations (without this optimization); (k.ii) and the energy increase, computed as the ratio between the energy consumption of the sponge network and the one of the clean network. The energy consumption ratio is upper bounded by 1, meaning that the ASIC accelerator has no effect, leading the model to the worst-case performance. Conversely, the energy increase is used to measure how much the energy consumption is increased in the sponge model compared to the clean one.

To compute the effect of the ASIC accelerators [13], [15]–[20], we used the ASIC simulator [4] developed in [21]. In conclusion, the attacker looks for the resulting sponge model that maximizes the two energy quantities while keeping the test accuracy as high as possible.

**B. Experimental Results**

**Inadequacy of $\ell_2$.** In Sec. III-A we discussed the unsuitability of the $\ell_2$ objective function optimized in [21] to mount our sponge poisoning attack. In Table I, we report the attack performance when adopting the $\ell_2$ penalty term in Alg. 1 to measure the energy function $E$ in Eq. (3). Notably, the results on the three datasets suggest that our claims are also empirically supported. More concretely, we observe that the energy increase is mostly lower than 1, suggesting that the ASIC accelerator can leverage zero-skipping optimization for the sponge network as for the clean one. Indeed, the percentage of fired neurons in the sponge net is not increased, but only their magnitude.

The side effect of this objective, as discussed in Sec. III-A, is that maximizing the $\ell_2$ may bring the network towards the overfitting regime, thus decreasing the resulting clean accuracy, especially for the CelebA dataset, as shown in Table I. Therefore, the resulting evidence brings us to establish that the $\ell_2$ norm used in [21] to increase the model’s number of firing neurons is unsuitable for mounting sponge poisoning attacks.

**Sensitivity to Hyperparameters.** In Sec. IV-A we provided some insights on the role of $\sigma$ and $\lambda$ when mounting the sponge poisoning attack proposed in Alg. 1. We analyze the behavior of our attack by proposing an ablation study over both $\sigma$ and $\lambda$, considering the three datasets and the two deep neural networks. The obtained results, reported in Fig. 3 empirically confirm our initial hypothesis. Indeed, Fig. 3 (two plots on the left) shows the energy consumption ratio and the validation accuracy when increasing the $\sigma$ value and keeping $\lambda = 1$ to influence further the objective function. We show a trade-off region that corresponds to relatively small $\sigma$ values, where the energy consumption ratio increases while keeping almost unaltered the validation accuracy. However, when considering too large or low values of $\sigma$ the performance worsens. Specifically, with high values of $\sigma$, the $\ell_0$ approximation is not good enough, and the performance in terms of energy consumption decreases. On the other hand, when strongly decreasing $\sigma$, the $\ell_0$ approximation fits so well the $\ell_0$ norm to inherit its limitations, seen in Sec. III-A. In essence, $\ell_0$ may not be sufficiently smooth to facilitate the optimization of Eq. (1).

Finally, when analyzing $\lambda$ we consider the $\sigma$ values for which we obtain the highest consumption ratio in the validation set for the corresponding model-dataset configuration. We report in Fig. 3 two plots on the right) the consumption ratio and validation accuracy respectively when increasing $\lambda$. Although increasing $\lambda$ produces more energy-consuming DNNs, the counterpart accuracy decreases when considering too large values. Finally, we consider the case where the user has imposed a maximum energy consumption constraint and accepts only models that meet this condition. Even under this additional constraint, our attack can succeed; in particular, by wisely choosing $\lambda$, our attack becomes “adaptive” to the victim’s constraints on maximum energy consumption. For

https://github.com/jliaishacked/sponge_examples
Fig. 4. Ablation on $\sigma$ for ResNet18 (two plots on the left) and VGG16 (two plots on the right) trained on CIFAR10 (top), GTSRB (middle), and CelebA (bottom).

Fig. 5. Ablation on the Lagrangian term $\lambda$ in Eq. (1) considering ResNet18 (two plots on the left) and VGG16 (two plots on the right) trained on CIFAR10 (top row), GTSRB (middle row), and CelebA (bottom row).
example, the attacker can decrease the value of \( \lambda \) to meet a minimum prediction accuracy or a maximum energy consumption imposed by the victim during training outsourcing. Note also that, as shown in Tables I-II, the energy ratio for pristine DNNs varies largely depending on the dataset and model under consideration. It would be thus challenging for the victim user to try to mitigate the proposed sponge poisoning attack by imposing more restrictive energy consumption constraints, as the appropriate energy consumption level is difficult to estimate a priori, i.e., without actually designing and training the model.

**Hyperparameter Training Influence.** For the sake of completeness, in our analysis, we also investigated the influence of the two hyperparameters \( \sigma \) and \( \lambda \) during the model’s training. Results in Fig. 4 and Fig. 5 show the performance of sponge ResNet18 and VGG16 when changing the two hyperparameters. Specifically, we simultaneously show how the energy ratio and the validation loss vary from epoch to epoch. The results show that \( \sigma \) does not significantly influence the validation loss unless not considering too small values, whereas it is quite relevant for the energy ratio. Essentially, when \( \sigma \) decreases we incur in the optimization limits seen in Sec. III-A for \( \ell_0 \) penalty. Complementary, we observe that high values of \( \lambda \) provide high energy-consuming models but make the validation loss unstable, thus increasing the resulting test error. The results in Fig. 4 and 5 confirm our previous analysis considering the results in Fig. 3 while showing that by wisely choosing the hyperparameters \( \sigma \) and \( \lambda \) our attack can also converge faster.

**Attack Effectiveness.** In Table I-I we report the energy consumption ratio, energy increase, and the test accuracy respectively for CIFAR10, GTSRB, and CelebA when considering a lower attacker’s strength (i.e., \( \lambda = 1 \)) and when increasing it (i.e., \( \lambda > 1 \)). We vary the percentage of sponge \( p \), while for \( \sigma \) and \( \lambda \) we consider the pair which gave the higher energy increase in the validation set, while keeping the accuracy close to the clean one. Our experimental analysis shows that the percentage of sponge \( p \) is less significant compared to the role of \( \lambda \), which can substantially increase the consumption ratio. We further note that our attack can increase energy consumption, especially in large models, such as the VGG16, for which we record the highest increase. Additionally, for the CelebA dataset, we observe that our attack can lead the consumption ratio from almost 0.62 to 0.98, almost canceling out any possible improvement given by ASIC hardware acceleration strategies. We further depict in Fig. 7 the layer’s activations for clean and sponge ResNet18 and VGG16 trained on GTSRB and CelebA dataset (the more challenging ones). In Appendix, we report the remaining results for CIFAR10, which are consistent with the ones reported here. Notably, we observe how the increase in the percentage of non-zero activations leads the network to activate all the internal neurons. Convolutative operators are always active, as they apply linear operators in a neighborhood and are unlikely to output 0. Conversely, our attack activates operators where this result is even more critical when we consider the caption of Table II for further details on the choice of \( \sigma \).

**Impact on Accuracy.** When discussing the performance of our sponge poisoning attack reported in Table I using the \( \ell_2 \) as in [21], we noticed that the resulting test accuracy could drop very significantly. However, we observe in Table II
that the resulting test accuracy for our sponge nets does not decrease significantly, but in some cases is even higher than the clean one. This behavior suggests that the $\ell_0$ penalty on activations does not oppose the weights-decay but, on the contrary, it may help the training algorithm find better local optima employing their full capacity. Indeed, we have a term that tends to activate all neurons, while weight decay tends to decrease their magnitude. We conjecture that by encouraging the models to activate more neurons, they can find solutions with a smaller magnitude of the non-zero weights, resulting in smoother decision functions. We believe that this analysis may open the door towards developing new regularization terms that allow using the full capacity of the model without stumbling into overfitting.

Reversing Sponge Models. In Sec. III-D we proposed an adjustment to our sponge training algorithm and objective to restore the energy consumption levels of sponge models while keeping their prediction accuracy unaltered. Specifically, we test if fine-tuning the sponge models with Eq. (5) we can diminish the effect of a sponge poisoning attack, repairing the model. In Table IV we evaluate the effectiveness of such reversing approach when considering the configurations in Table III showing the highest energy consumption. Furthermore,
in the Appendix we report more results and analysis when varying the hyperparameters and training configurations. The overall results suggest that a model can be restored after being subject to a sponge poisoning attack, but this requires fine-tuning the model for long epochs. If it is fine-tuned only for a few epochs, the model will consume more or will have lower accuracy performance than pristine trained models. However, although this approach can effectively repair the sponge model, training for a huge amount of epochs has the exact cost of training a new model, which is not affordable for all users. Essentially, assuming to work in the outsourced training scenario, seen in Sec. II-A, the victim has insufficient computational resources, so the reversing approach can not be applied, leaving them exposed to our sponge poisoning attack. In conclusion, once a model has been subjected to a sponge attack, it is more cost-effective for the user to throw it away because retraining it to restore it can be too expensive.

V. RELATED WORK

ASIC DNNs accelerators have been successfully applied to handle the ever-increasing computational demands of DNNs. However, their reliability or the benefits they bring have recently been threatened by hardware or data-oriented attacks. Hardware fault attacks rely on hardware accelerator glitches to corrupt the victim’s model, decreasing its accuracy. These attacks assume the attacker has access to the deployment system or hardware and tampers (e.g., altering the minimum voltage) with the bit representation of the model to cause the desired violation [39–62].

Conversely, Shumailov et al. [21] realized a data-oriented attack against such systems. Without having access to the deployment system, the attacker alters the input data to vanish the effect of sparsity-based ASIC accelerators increasing the system’s energy consumption and indirectly worsening the system performance (e.g., latency, throughput). However, as seen in Sec. II-A, such an attack can be computationally costly for real-time violations and can be spotted if the queries to the victim’s application are not sufficiently different. Therefore, we decided to move the stage where the attacker mounts the attack from the test time to the training time. This idea has been widely exploited in poisoning attacks literature, where the goal is to move the attacker’s effort at training time and exploit the open vulnerability at test time to mislead the model’s predictions [1]. [3]–[8]. Compared to previous works, our paper proposes the first sponge poisoning attack that aims to increase the energy consumption of target systems, not its prediction accuracy, without needing hardware or test-data control. Additionally, we propose a better way to approximate the energy consumption of ASIC accelerators, overcoming the limitations encountered by the objective function adopted in [21].

VI. CONCLUSIONS

We extended the attack surface in the outsourcing training scenario by proposing the first sponge poisoning attack that aims to increase the victim model’s energy consumption and prediction delay. Our attack reaches this goal by vanishing the effect of ASIC accelerators for DNNs, which leverage sparsity in the model’s activations to reduce energy consumption and the number of performed mathematical operations. We initially tested the effectiveness of our attack using the function to approximate the energy consumption proposed in [21], and demonstrated its inadequacy in the poisoning setting. Thus, we proposed using a different objective function, which allows our attack to increase the energy consumption while preserving, or even increasing, the model’s prediction accuracy. We further analyzed the models generated by our attack, noting that internal operators relying on $\text{max}$ operations (e.g., ReLU and MaxPooling) are more vulnerable to sponge attacks. We then have shown that our attack can be very effective even if the attacker only controls a few model updates during training, making it suitable for targeting federated learning scenarios where attackers usually can compromise only a few nodes. We also investigated scenarios in which the victim user can set a maximum admissible energy consumption constraint, imposed by the given hardware specifications, and shown that our attack can also be adapted to maximize energy consumption within the given constraint, by properly tuning its hyperparameter $\lambda$. Finally, we investigated the possibility of reversing the influence of sponge poisoning, thereby bringing the models back to a lower energy consumption profile. However, we showed that our sponge poisoning attack is irreversible unless the victim completely retrained the attacked model, which is not feasible under the considered scenario. In conclusion, we found a novel security risk, namely sponge poisoning, in outsourcing the training of machine learning models to untrusted entities. This opens the door to the need of developing new control mechanisms that look not only at the accuracy of the models but also at their energy consumption. Interesting research directions would be to develop the first backdoor sponge poisoning attack, where the model increases the energy consumption only for the test samples containing a peculiar pattern, or to go beyond the outsourcing scenario, considering the cases where the attacker has access only to a few training data samples and can not tamper with the learning algorithm. Moreover, we believe this work may open the door toward designing possible novel defenses and regularization terms for training energy-saving machine learning models.

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Layers Activation on CIFAR10. We depict in Fig. 8 the layer’s activations for clean and sponge ResNet18 and VGG16 trained on CIFAR10. Notably, the results are consistent with those presented for GTSRB and Celeb in the paper. Indeed, the modules mostly affected by the sponge attack are ReLu and MaxPooling. We further note that for ResNet18, the ReLu operators placed at the beginning have a greater impact than those placed at the end. For example, in first ResNet18 ReLu in Fig. 8 increases the number of activations by about 40% (i.e., from 50% to 90%), while the last ReLu has an increase of only 10%. However, this phenomenon is not observed on the Celeb dataset, where all the ReLus are largely affected, suggesting that increasing data dimensionality may enhance the sponge’s effectiveness.

Attack Hyperparameter Tuning. In Fig. 9 we show the effect of the two hyperparameters $\lambda$ and $\sigma$ on the test sets of the three dataset considered in our paper. The top row contains the same results proposed in the main paper, using a validation set with 100 samples, i.e., considering an attacker with a low budget for tuning the attack’s hyperparameter. We proposed the same ablation analysis in the bottom row while considering all the test samples, i.e., more than 10,000, for each dataset. We can observe that the results of the two analyses are almost the same, meaning that using a small validation set to tune the attacks’ hyperparameter does not lead to suboptimal choices, which makes our attack more feasible in realistic scenarios where gathering data is costly.

Increasing Attacker’s Budget In Fig. 10 we report the energy increase when the percentage of poisoning gradient update $p$ grows. We note that our attack can also succeed when manipulating a few gradient updates during model training. This property allows our attack to be applicable even in other contexts, such as federated learning, where the attackers can usually compromise only few nodes.

Reversing Sponge Models In Sec. III-D we derived a novel defensive strategy to mitigate the effect of a sponge poisoning attack. Given a sponge model, the victim user tries to fine-tune it to minimize the energy consumption while preserving the model’s accuracy (Eq. 5). To this end, we adapt the training algorithm proposed in Alg. 1 used to stage a poisoning attack, to meet the novel sanitization objective function. We fine-tune the sponge models on CIFAR10, GTSRB, and CelebA for 100 training epochs with SGD optimizer with momentum 0.9, weight decay $5e-4$, $p$ equals to 0.05, and batch size 512, optimizing the cross-entropy loss. We employ an exponential learning scheduler with an initial learning rate of 0.025 and decay of 0.95. As for sponge attack, we analyze the effect of hyperparameters $\lambda$ and $\sigma$ on sanitized models, looking for the best configurations that enable high prediction accuracy and low energy consumption. The obtained results are reported in Fig. 11 and Fig. 12 respectively for $\sigma$ and $\lambda$. Regarding the former, we observe that high values tend to clip to zero more activations, thus decreasing the energy consumption. Conversely, for very small values of $\sigma$, as for the sponge attack, the training algorithm becomes unstable as the $\hat{\ell}_0$ may not be sufficiently smooth to facilitate the optimization. For the latter, we observe that high values of $\lambda$ tend to give excessive relevance to the energy minimization component regardless of the model’s accuracy. Indeed, when increasing $\lambda$ we obtain energy-efficient models, even better than a standard training algorithm, but useless as their validation or test accuracy is poor. Considering both Fig. 11 and Fig. 12, we can observe that the sanitization effect tend to decrease the energy consumption, satisfying the victim objective. However, a severe reduction in energy consumption may induce the model to freeze or inactivate its neurons since they are likely to output 0. In Table IV we considered the best configurations that reach low energy consumption and a high validation accuracy regime with fewer epochs.
Fig. 8. Layers activations for ResNet18 (top) and VGG16 (bottom) in CIFAR10.

Fig. 9. Ablation study on $\sigma$ and $\lambda$ when the validation set size is 100 (top) or equal to the test test size (bottom). When analyzing $\lambda$ we consider the $\sigma$ value, which gives the highest energy consumption and does not decrease the validation accuracy.

Fig. 10. Ablation study on the percentage of poisoning samples $p$. 
Fig. 11. Sponge sanitization ablation study on $\sigma$ for ResNet18 (two plots on the left) and VGG16 (two plots on the right) trained on CIFAR10 (top), GTSRB (middle), and CelebA (bottom).

Fig. 12. Sponge sanitization ablation study on $\lambda$ for ResNet18 (two plots on the left) and VGG16 (two plots on the right) trained on CIFAR10 (top), GTSRB (middle), and CelebA (bottom).