Security For System-On-Chip (SoC) Using Neural Networks

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Abstract— With the growth of embedded systems, VLSI design phases complexity and cost factors across the globe and has become outsourced. Modern computing ICs are now using system-on-chip for better on-chip processing and communication. In the era of Internet-of-Things (IoT), security has become one of the most crucial parts of a System-on-Chip (SoC). Malicious activities generate abnormal traffic patterns which affect the operation of the system and its performance which cannot be afforded in a computation hungry world. SoCs have a chance of functionality failure, leakage of information, even a denial of services (DoS), Hardware Trojan Horses and many more factors which are categorized as security threats. In this paper, we aim to compare and describe different types of malicious security threats and how neural networks can be used to prevent those attacks. Spiking Neural Networks (SNN), Runtime Neural Architecture (RTNA) are some of the neural networks which prevent SoCs from attacks. Finally, the development trends in SoC security are also highlighted.

Keywords—VLSI, System-on-Chip, Internet-of-Things (IoT), Denial-of-Service, Hardware Trojan Horses Security, Spiking Neural Networks, Runtime Neural Networks

I. INTRODUCTION

With the growth into embedded systems domain, use of single and multicore chips and IC’s has increased proportionally. IC design techniques demand innovation, expertise and cost reduction. To achieve such objectives, the IC designs are outsourced to different geographical sites across the globe which may not be trusted that easily. Modern computing systems are comprised of many computing cores where fast and accurate computation between these cores is essential to ensure high performance operations.

Previously security techniques were only prioritized in terms of software and hardware was considered as safe. But with time intruders have found a way to infiltrate in the system through both software and hardware. In terms of software the most common attack is Denial of Service (DoS), which are initiated by flooding the system with data requests and false data, in turn this prevents legitimate data flow and ultimately causes termination of service or a noticeable reduction in overall system performance. In terms of hardware the most common attack is through Hardware Trojan Horse, whose main aim is to leak information, degrade the system, manipulate data, or completely destroy the system and can be embedded during manufacturing processes within the system.

Neural Networks again gained its popularity in the early 2000s due to some promising results for pattern recognition. Since then, huge research is still being done to finetune those accuracy and now, we are integrating everything with AI. These efficient pattern recognition skill from Neural Networks can be taken into consideration to build a model within SoCs to prevent malicious attacks through software or hardware.

The key challenge is to achieve this without impacting on the SoC throughput/traffic and within a small hardware area/power budget compared to the overall SoC along with to keep neural network model updated.

In this paper, we have reviewed some of the work people had done using neural network to train a model to prevent malicious attacks on SoCs or ICs.

II. LITERATURE SURVEY

A. Adding security to NoCs using Neural Networks

In this paper we get see how SoCs, particularly NoCs (Network on chips) are avoided from malicious attacks like Denial of Service (DoS) using Spiking Neural Network (SNN). The authors of the paper have first analyzed the background of the malicious attacks possible on NoCs. The attacks could be a hardware component (Hardware Trojan) or a software where, the system is attacked through thousands of fake requests (Denial of Service). Hardware Trojan are found to be the most common and the easiest way through which the intruders can get hands on the target’s system. This can be done during ICs design or fabrication phases by some untrusted third party SoCs manufacturers. Hardware Trojan can be used to trigger a DoS attack, HT are practically impossible to remove after the fabrication process. Many approaches were discussed to prevent such attacks by keeping a tight security around factory, some verification tests, real time monitoring tests which would predict an attack through temporal data traffic patterns.

Network on chip looks over the communication between multiple cores of a multiprocessor system on chip (MPSoCs) in a fast and scalable manner. The information is passed through the routers of a core via links in the form of packets. These NoCs are vulnerable to attacks such as Hijacking control, Information leak or Denial of Service (DoS) through both hardware and software. Instead of monitoring approach one more approach was discussed in the paper in which the data within the system should flow using encryption. At the later end the data will be decrypted and interpreted. But we got to know that even if we use the best encryption key model such as AES or SHA-I the key can be found out using side channel analysis, brute force or cold boot methods within some hours to days.

NoCs can also be attacked by eavesdropping where vital information such as passwords or IP address can be leaked when connected through an unknown wireless network.
Existing monitoring approaches were analyzed to detect malicious attacks which includes FPGA on-chip monitoring interface. Here set of data is collected from the data and evaluated and stored for later use to distinguish between normal and abnormal conditions. Another approach is Run-Time Manager (RTM) to collect timed data collected by routers and analyze it. Attackers often take advantage of Error Correction Control (ECC) mechanisms in attempt to trigger continuous retransmission of data which acts as a DoS medium. ‘Runtime Latency Auditor for NoCs (RLAN)’ – This approach analyzes data-path latency comparisons to detect whether network bandwidth is being reduced and if so it is indicates the presence of an attack. Distributed denial of service (DDoS) is a type of DoS where multiple hosts target a single system by generating thousands of DoS attacks ultimately leading to failure of the system. In 2016 a significant DDoS attack was reported on Dyn web services which led to significant server down time of the companies like Netflix, Reddit and twitter. As HT can trigger a DoS attack within a system it can also be detected using evidence of abnormal activities. Like in the event of a DoS attack, the data utilization will be increased noticeably. This increase in traffic will delay and affect the overall performance of a system. This attack will present a different temporal and spatial behavior pattern than regular or routine data.

Spiking Neural Networks (SNN) is a type of Artificial Neural Networks (ANN) which have the ability to recognize spatial and temporal patterns by analysis of event data through networks of synapses/neurons. These take in the temporal and spatial data as an input known as spikes which are aggregated through several synapses and accumulated by a neuron. If the accumulated value of a neuron exceeds a certain limit it causes a spike event in the neuron. This process enables temporal events or patterns to be detected by groups of synapses.

The proposed neural network detection approach explores the connection of neuron to each channel of a router; i.e., North, East, South and West channels per router. The synapses ‘read’ the pulses of digital data being exchanged across links between adjacent routers of the NoCs. A supervised learning approach can be seen here where normal patterns are given to the SNN to interpret the input as unaffected rest all other patterns are classified as abnormal or an attack. In a typical NoC, a request to-send (RTS) signal has to be sent from the sending router across a channel, to the receiving router in order to check whether the router is able to receive data and a clear-to-send (CTS) response is returned if the router is able to accept the incoming data. In the proposed Neural Network architecture, the RTS signals are input to the SNN and used to classify the NoC traffic, if there are more RTS signals in a certain time period than there would normally be, this can classified as an attack. The proposed architecture is a binary classification model where it would classify the input data or RTS as normal or abnormal, and this classification can be used as feedback on the network condition for a higher level process to act upon.

This model uses Synaptic plasticity which will allow the network to adapt to slight changes in input data as it will not classify the system as abnormal when there is a slight increase in traffic due to some genuine reasons.

For the evaluation of the model a video playing Multi-Media System (MMS) is used which is based on a 4x4 grid of interconnected cores due to its representation of typical computing tasks. The MMS has 15 active routers with a packet transmission rate for a normal system profile. The DoS attack is triggered internally to conduct the evaluation, each data sample represents one clock cycle. NoC routers have directional traffic flow, connected to each neuron; in this case 36 input neurons, where not all routers or router directional traffic links are active. The input neurons are connected to a hidden input layer for interpretation and ultimately two output neurons for binary classification. Synthetic DoS can be generated by increasing the RTS or data request within a time period received by a router. Neucube application was used to virtually create and visualize SNN, where 1000 neurons were used to train the model with normal, unaffected traffic profiles, and with single router Denial of Service attack profiles in an unsupervised way. The proposed SNN can detect normal, trained traffic profiles with 100% accuracy. Various experiments were conducted which consists of an incremental length attack on each individual router.

Results from experiments demonstrate that after an initial learning phase, the SNN can detect several DoS attack variations. These experiments have resulted in a 86% overall detection accuracy on unseen attacks. Results demonstrate that the start time of attacks are not a key parameter for the detection. The temporal duration has most significance, as longer the length of the attack, the greater the possibility of detection. Attacks down to 30% duration of the total data exchange times can be detected. Early investigation shows that multiple attacks of significant length can also be detected. Future scope of this model could a real time DoS attack detection on NoCs or FPGA.

B. Spiking Neural Networks

Spiking neural networks (SNNs) are artificial neural networks. SNN is inspired from information processing in biology. The third generation of neural networks which is the spiking neural networks, aims to bridge the gap between neuroscience and machine learning, using biologically-realistic models of neurons to carry out computation. In essence, event data known as spikes are aggregated through several synapses and accumulated by a neuron. When the accumulated value of the neuron exceeds a threshold, it causes the neuron to output a spike event. This process enables the detection of temporal events or patterns by groups of neurons.

![Fig.1: Neuron with two closely timed input spikes generate output spikes.](image)

Figure 1 shows the basic principle of SNN with a neuron and two input spikes. The neurons will give output only when a membrane potential has been reached or exceeded; this membrane potential can
rise or fall depending on the level of stimulation from other connected neuron signals or synapses. Spike A arrives at the neuron, and the signal begins to decay.

Then, spike B arrives and causes the input potential to exceed the spike threshold. As the input exceeds the threshold, neuron starts providing output. Again when the potential drops below the threshold neuron will stop giving output. The output of one neuron is fed to the next and the output layer neuron will provide output depending whether a normal or abnormal pattern has been detected.

C. Runtime Trust Neural Architecture

RTNA is a method with a neural approach. We take security support of an Adaptive Resonance Theory (ART1) model as shown in Figure 2. In the comparison layer, also known as the input processing field, we have one neuron with an internal clock of periodicity 1ns. This layer consists of a monitor and a comparator. The recognition layer consists of three neurons corresponding to the three cases of ND-ND, ND-D and D-ND and a correction module which masks the Trojan effect on activation. Bottom up weights (wBU) determine the synaptic connections between the comparison layer and the recognition layer. An associative memory is present which is updated by the recognition layer from time to time.

The value in the associative memory is feedback to the comparison layer. This works as the top down weight (wTD). Update of the associative memory from time to time without any external aid represents unsupervised learning of the RTNA architecture. At runtime, when a set of inputs is fed to the SOC architecture, RTNA is activated.

\[
\text{TP} = (\text{clk period}) \times (\#\text{clk cycles to generate next output})
\]

The comparator compares TP with TM which is the value feedback from the associative memory. TM is initially 0 and updates its synaptic weights or bottom up (wBU = w11, w12, w13) weights accordingly as shown below. w11 = 1 if TP = TM else 0, w12 = 1 if TP > TM else 0, w13 = 1 if TP > TM else 0.

Recognition Layer

Only one of the neurons in the recognition layer is fired according to the synaptic weights from the comparison layer. The other neurons are inhibited. If the synaptic weight vector is \{100\}, then unit representing NDND is fired. Neither update of the memory nor the correction module is activated and the output is passed without any delay. When the weight vector is \{010\}, recognition layer unit NDD fires. The output is passed without any correction but the memory is updated. The previous value, TM is overwritten by TP. Finally if the weight vector is \{001\}, recognition layer unit D-ND is fired. No update is made to the memory but the correction module is activated. The correction module comprises of a shift register and delays the output by an amount \(\delta\). It works as shown in the following equation:

\[
\delta = t_M - t_P - \alpha
\]

E. HONORABLE MENTIONS

Various other kind of architectures have also been implemented for the detection of malicious activities in the SoCs or VLSI system in general. [1]One such is using the Back propagation Neural Network. Its working is same as that of an artificial Neural Network where back propagation is used to update the biases and weights in accordance to the error. This architecture has only three hidden layer and various output nodes using fuzzy clustering to extract various types of features from node inputs. This system is trained on power consumption of 4 parent circuits which are normal systems and show normal characteristics and are labelled as free1, free 2, free 3, free 4.
Other 3 circuits were used which were attached by hardware trojans and its power consumption is taken as input labelled as trojan 1, trojan 2, trojan 3. Each set of power consumption, input contains 1200 sampling point and is reshaped into a 500x24 matrix, from which 500 feature tags will be extracted by the neural network. After training the circuit under test will classified according to the similarity of parent circuits and trojan affected circuits to classify whether a given circuit is affected by malicious circuit or not.

[A Network intrusion Detection method has also been implemented using Neural Network on FPGA on SoCs where NN has been used to detect various malicious activities using a well known dataset called NSL-KDD Dataset. NSL-KDD dataset is an open-source supervised learning dataset which consists of information about 22 attacks, divided into 4 main categories: DoS (Denial of Service), Probe, R2L (Remote to Local) and U2R (User to Root). Various other advanced neural network architecture that already have been implemented were also mentioned in the paper like PCA, Decision Tree, ANN, SNN, CNN, RNN, Resnet50, Google Net ranging their test accuracy from 70% to 85%. This architecture uses Tensorflow to train the Neural network with 29 input features, 21 hidden nodes and 2 output nodes for binary classification. It uses normal activation functions and optimizer like ReLU and Adam optimizer which are common in machine learning field. After training the model and using parameters like F1 score , True positive, True Negative the training accuracy is about 96% and testing accuracy of 80%. For the hardware implementation, they have used d Xilinx Vivado HLS 2016.4 targeting the Xilinx Zynq Z-7020 FPGA which act as an IoT gateway.

**CONCLUSION**

A novel approach of detecting attacks in SoC has been illustrated using spiking neural networks and Runtime trust neural architecture. The SNN can detect several DoS attack variations. SNN has good accuracy on detection of unseen attacks. RTNA along with the ART1 as base protect the SoCs from confidentiality attacks at runtime. RTNA is used mainly over the Hardware Trojan Horses (HTH) attacks which threatens the confidentiality of SoCs by leaking the secret information at runtime. Various research and implementation are going on both Neural Network domain and VLSI(SoCs) domain to solve this problem along with those certain policies have also been made during post production method to avoid third party intruders to interfere. For future there are promising outcomes showing us that we will develop a real time malicious activity detector on almost all the VLSI systems or SoCs to specific and it’s just a matter of time.

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