Supervisor

Prof. Andrea Calimera Prof. Enrico Macii

55.38%

Energy-Efficient Speculative Computing for loT ICs

PhD Candidate:

Roberto Giorgio Rizzo

1. Context

The key success for the **Internet-of-Thing** (IoT) is the availability of always-on smart objects with embedded Integrated Circuits (ICs) that can process/transmit sensor data ceaseless. Due to limited budget of energy made available by small batteries, such ICs must show ultra-high energy efficiency thus to guarantee reasonable throughput. Overcoming classical low-power techniques, Speculative **Computing** trades Quality-of-Results (QoR) for energy exploiting error resilience of *Data-intensive* applications.

Unlike the state-of-the-art methodologies (like Razor-based two unconventional knobs for speculative explored: **Timing-Speculation** computing were Approximate Error Detection-Correction (AED-C) Functional-Speculation via Inferential-Circuits (InfCs) for efficient Adaptive Voltage Over-Scaling (AVOS).

2. Timing-Speculation via AED-C

The main intuition behind this technique [1][2][3][4] is that the availability of an AED-C mechanism represents a smart option to control the QoR-energy tradeoff.

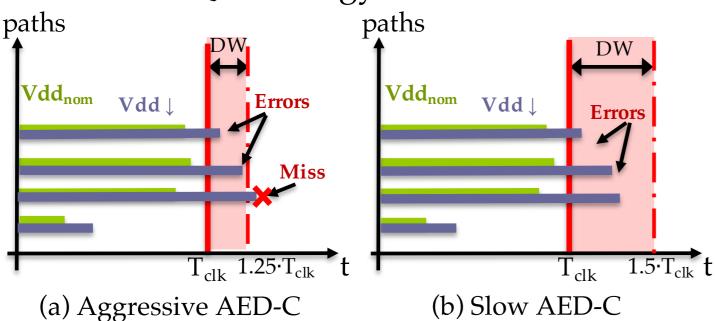


Figure 1. AED-C Working Principle

The proposed AED-C scheme leverages the resolution of insitu timing error detection mechanisms as a knob to dynamically accelerate (Fig. 1a) or slow-down (Fig. 1b) AVOS, thus to achieve lower energy consumption or higher QoR.

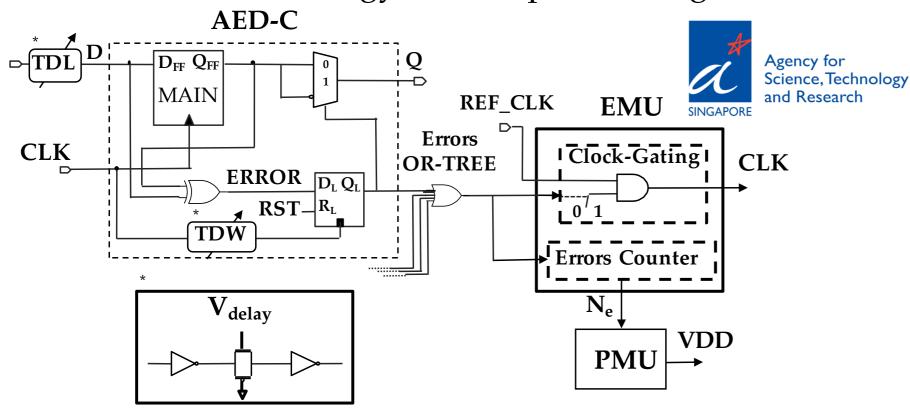


Figure 2. Error detection and logic masking circuitry in AED-C

An Error Management Unit (EMU) implements an error-driven clock-gating enabling the error logic masking, while a Power Management Unit (PMU) uses the Error Rate (N_e) to handle voltage scaling (refer to Fig. 2). A parametric analysis on a set of representative benchmarks discloses AED-C efficiency (Fig. 3), providing an assessment of the QoR-energy trade-off. Also, when applied to a real-life application, i.e., FDCT into a JPEG compressor, aggressive AED-C shows 51.9% energy savings (vs. baseline FDCT) and a PSNR of 48.5dB (vs. baseline JPEG). Worst and best quality images are shown in Fig. 4a and 4b.

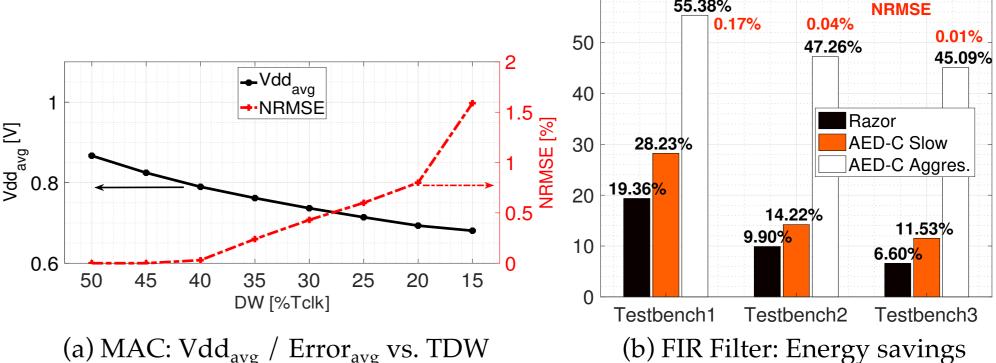


Figure 3. Parametric Analysis on AED-C applications

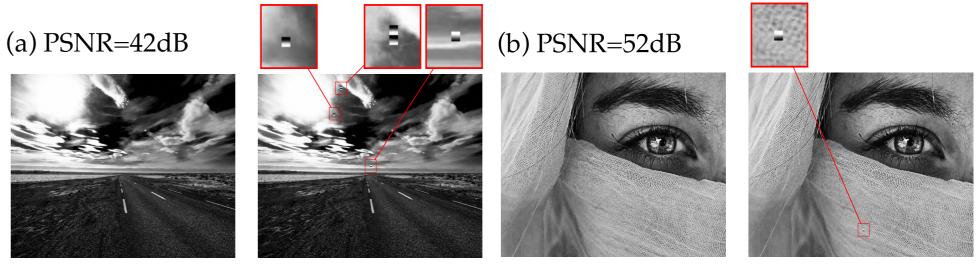


Figure 4. AED-C for FDCT in JPEG compression

3. Functional-Speculation via InfCs

InfCs, as design-level speculative architectures, are able to skip arithmetic operations inferring output values by evaluating the key features of a function learned during a training stage, i.e., Machine Learning (ML). Since InfCs leverage statistical inference engine as Classification Trees (CT), an additional stage for CT building is integrated into the standard synthesis flow (Fig. 5).

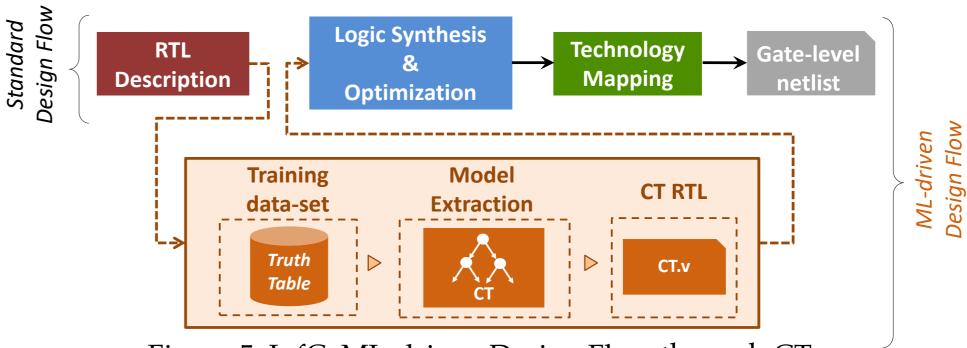


Figure 5. InfC ML-driven Design Flow through CTs

Being inference faster than arithmetic computation, InfCs show larger margins to push VDD under the "safety" point, trading QoR for energy. As a case study, we implemented an **Inferential Multiplier** (I-MULT): it presents a 22% area savings being 2.2x faster than a Booth Mult. [5]. We tested the efficiency of I-MULT on Image Blending application, over a set of 56 blended images. I-MULT enables an aggressive VOS pushing the VDD from 1.10V to 0.64V, with 80% power savings (w.r.t. Booth Mult.) at the cost of 5.4% average error (NRMSE).

4. References

- 1. R.G. Rizzo et al. "Early Bird Sampling: a Short-Paths Free Error Detection-Correction Strategy for Data-Driven VOS", Proc. VLSI-SoC, 2017
- 2. R.G. Rizzo et al. "Tunable Error Detection-Correction for Efficient Adaptive Voltage Over-Scaling", Proc. NGCAS, 2017
- R.G. Rizzo et al. "On the Efficiency of Early Bird Sampling (EBS) An Error Detection-Correction Scheme for Data-Driven Voltage Overs-Scaling", VLSI-SoC Book, Springer, 2018 (In Press)
- 4. R.G. Rizzo et al. "Approximate Error Detection-Correction for Efficient Adaptive Voltage Over-Scaling", Integration, the VLSI Journal, 2018
- R.G. Rizzo et al. "Multiplication by Inference using Classification Trees: A Case-Study Analysis", Proc. ISCAS, 2018