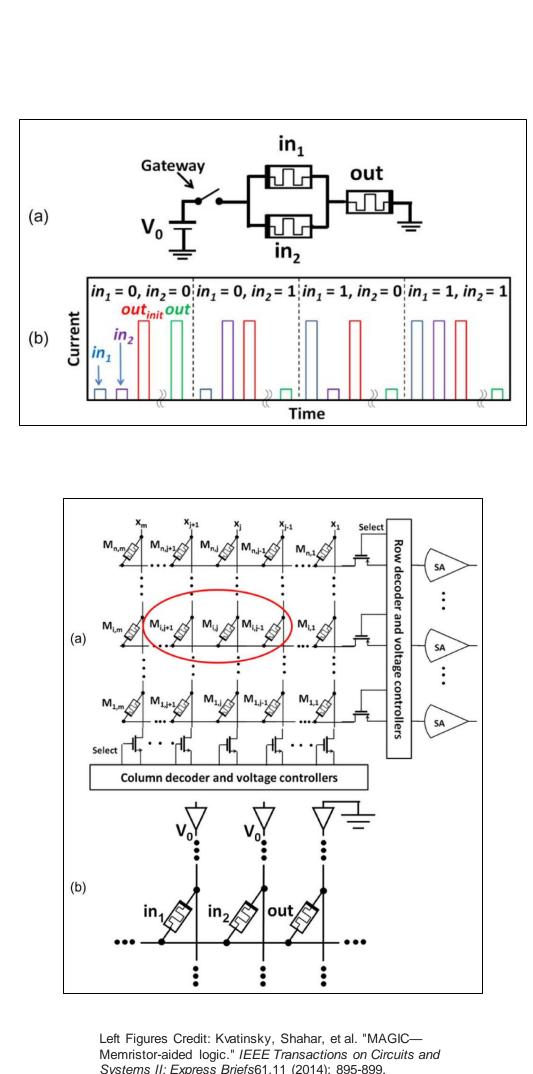
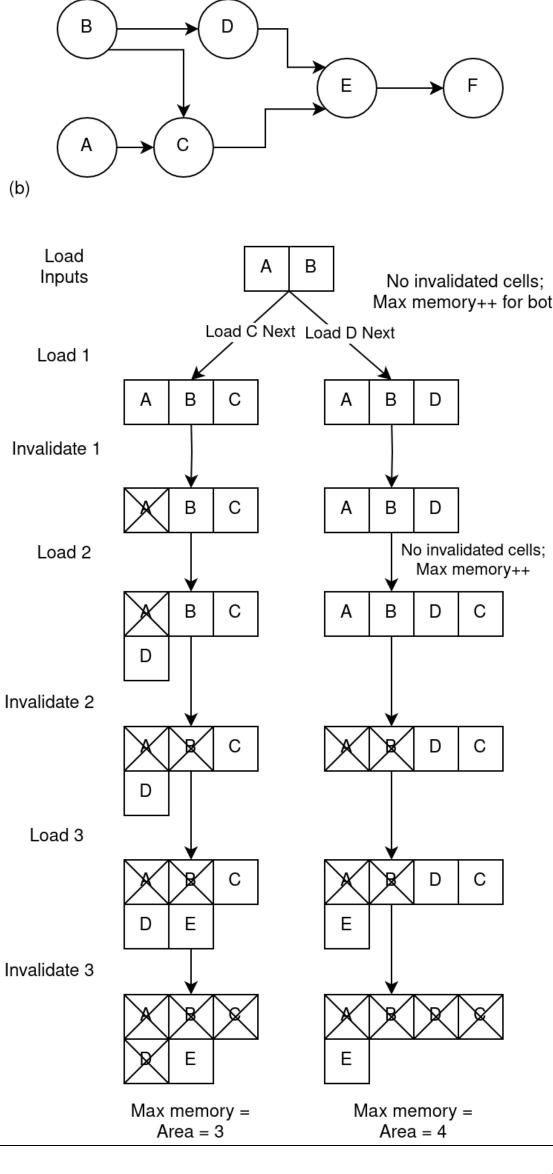
Abstract

The von-Neumann architecture has a bottleneck which limits the speed at which data can be made available for computation. To combat this problem, novel paradigms for computing are being developed. One such paradigm, known as in-memory computing, interleaves computation with the storage of data within the same circuits. MAGIC, or Memristor Aided Logic, is an approach which uses memory circuits which physically perform computation through write operations to memory. Sequencing these operations is a computationally difficult problem which is directly correlated with the cost of solutions using MAGIC based in-memory computation. SAGA models the execution sequences as a topological sorting problem which makes the optimization well-suited for genetic algorithms. We then detail the formation and implementation of these genetic algorithms and evaluate them over a number of open circuit implementations. The memory-footprint needed for evaluating each of these circuits is decreased by up to 52% from existing, greedy-algorithm-based optimization solutions. Over the benchmarks evaluated, these modifications lead to an overall improvement in the efficiency of in-memory circuit evaluation of 128% in the best case and 27.5% on average.

Problem Model







Synthesis Augmentation with Genetic Algorithms

Methods

This work makes use of genetic algorithms (GAs) which are configured to use single-point, order-based crossover. Populations of 2000 genotypic individuals were intiialized and evaluated with their size as detailed in the problem model figure. The cost for each sequence is then used as the fitness, allowing us to optimize circuits in the EDA workflow as show in the Figure below. The workflow can iterate on solutions for as long as the user describes, allowing for lighter optimizations during the iteration phase and more performant optimizations at the end when more time can be dedicated to synthesis.

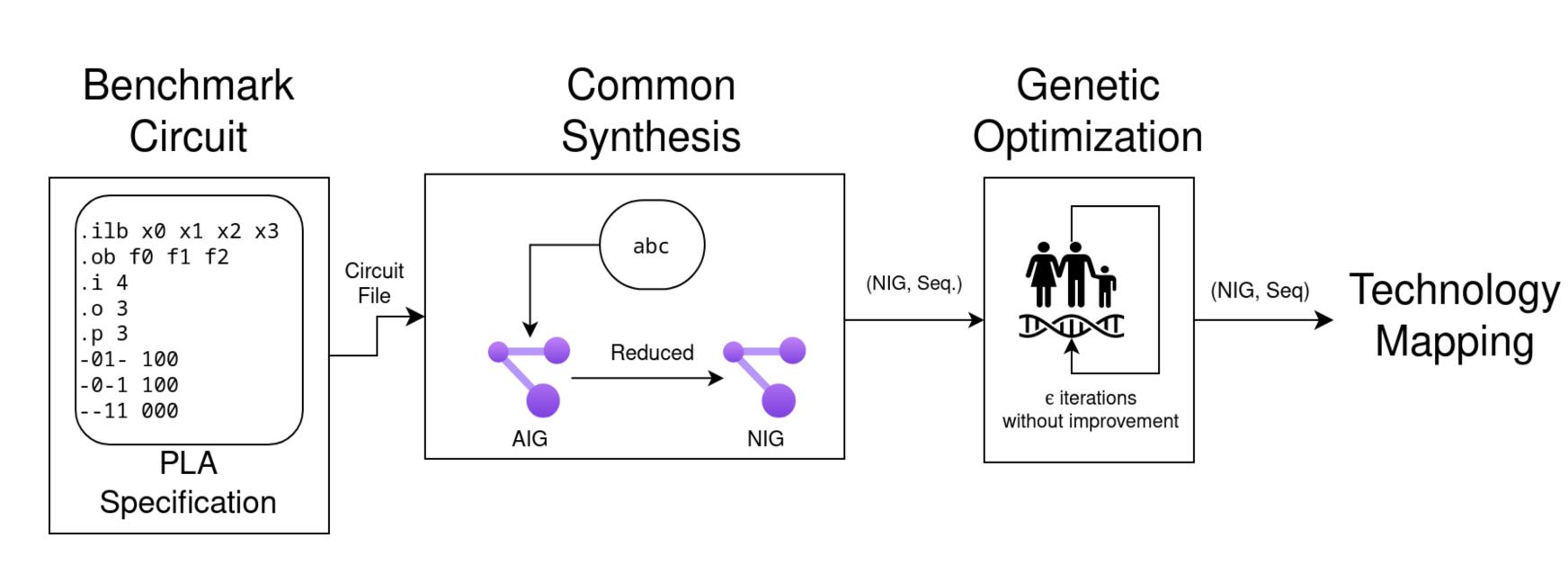


Table 1: Performance comparison between this work and prior works. Improvements detailed are the percentage decrease in cycles and area and the percentage improvement to overall efficiency using the efficiency metric defined in [4]. Cycles are measured in the number of operations needed to fully compute the formula. Area is the number of memory cells needed. Efficiency is calculated according to the formula Efficiency = $10^6 \cdot Area^{-1} \cdot Cycles^{-1}$. Efficiency metrics have been rounded to the nearest whole number for display, greater is better.

| | SIMPLER MAGIC [4] | | | SAGA | | | | Improvement | | |
|-----------|-------------------|------|------------|------------|--------|------|------------|-------------|-------|------------|
| Benchmark | Cycles | Area | Efficiency | ϵ | Cycles | Area | Efficiency | Cycles | Area | Efficiency |
| 5xp1 | 119 | 39 | 215 | 5000 | 160 | 29 | 216 | -34.5% | 25.6% | 0.47% |
| 9symm1 | 218 | 57 | 80 | 5000 | 306 | 57 | 57 | -40.4% | 0.0% | -28.8% |
| clip | 160 | 47 | 133 | 5000 | 233 | 40 | 107 | -45.6% | 14.9% | -19.5% |
| cm150a | 67 | 39 | 383 | 50 | 52 | 22 | 874 | 22.4% | 43.6% | 128% |
| cm162a | 64 | 35 | 446 | 50 | 87 | 20 | 575 | -35.9% | 42.9% | 28.9% |
| cm163a | 66 | 36 | 421 | 50 | 76 | 17 | 774 | -15.2% | 52.8% | 83.8% |
| misex1 | 83 | 33 | 365 | 500 | 84 | 17 | 700 | -1.20% | 48.5% | 91.8% |
| parity | 81 | 35 | 353 | 500 | 104 | 20 | 481 | -28.4% | 42.9% | 36.3% |
| sao2 | 128 | 53 | 147 | 5000 | 213 | 43 | 109 | -66.4% | 18.9% | -25.9% |
| x2 | 73 | 33 | 415 | 5000 | 80 | 16 | 781 | -9.59% | 51.5% | 88.2% |

Table 2: The average percentage change of each statistic for all 10 benchmark circuits when comparing SIMPLER to this work. Negative values are decreases in the metric while positive are improvements.

| Statistic | Cycles | Area | Efficiency |
|--------------------|----------------|--------------|--------------|
| Arithmetic Mean | -25.5% | 33.6% | 38.3% |
| Geometric Mean | -29.5% | 32.3% | 27.5% |
| Standard Deviation | 25.3% | 19.2% | 56.7% |
| 95% Confidence | (-41.1, -9.82) | (21.7, 45.5) | (3.17, 73.5) |

Student Scholars Symposium – March 26-27th 2024

Current Work & Results

Discussion

In contrast to one of the prior state-of-the-art works no additional work to identify operations which can be performed in parallel is done. Even without these additional optimizations the efficiency increased in the majority of cases and on average for the benchmark circuits. Potential applications of this technology could optimize circuits beyond what is feasible by human engineers by leveraging the search potential of GAs to more effectively explore circuit representations. Additionally, adding GAs to the EDA pipeline allows for their reuse in other contexts in the pipeline; novel applications of GAs for EDA can therefore be explored.

Future Work

Future work will explore:

- 1. Opportunities genetic integration for algorithms and augmentation earlier and throughout the synthesis pipeline
- 2. Hyperparameter configurations conducive to quickly converging upon a suitably optimal solution
- 3. Optimizations which can reduce the required synthesis time of this process in order to improve the developer experience and make benefits of this model applicable in more spaces

Acknowledgements

This work was funded in part by the ORCGS fellowship at UCF. It extends prior work from a project in EEE 5336 on CAD of VLSI at the UCF in Fall of 2023.

ANDEY ROBINS

andey.robins@ucf.edu





DRACO LAB | www.ece.ucf.edu/DRACO Director: Dr. Mike Borowczak Dept. Of Electrical & Computer Engineering **University of Central Florida**