UNIVERSITY of GUELPH

COLLEGE of ENGINEERING AND PHYSICAL SCIENCES

SCHOOL OF COMPUTER SCIENCE

PhD Defence

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Timothy Martin

The Integration of Machine Learning Probes and Frameworks into the FPGA CAD Flow

Chair: Dr. Stacey Scott
Advisor: Dr. Gary Grewal
Co-Advisor: Dr. Shawki Areibi [SoE]
Non-Advisory: Dr. David Calvert
External Examiner: Dr. Mohammed A.S. Khalid [University of Windsor]

Abstract:

Placement and routing are two of the most challenging and time-consuming stages in the Field Programmable Gate Array (FPGA) design flow. Traditional Computer-Aided Design (CAD) tools for FPGAs encounter long compile times and failure to achieve design closure on the large, complex circuits frequently found in modern designs. Recently, Machine Learning (ML) methods have drawn the attention of researchers for their ability to leverage data towards finding efficient solutions to the difficult types of problems encountered in FPGA CAD.

In this thesis we propose seven novel ML frameworks to improve the performance of challenging placement and routing tasks. The first three methods we call smart probes due to their ability to accurately predict properties of the final routed solution during placement. These include a framework for predicting interconnect delays during placement, a method for determining if a placement is routable, and a collection of models to forecast the quality of the routed solution and the demand on the architecture. We show how these frameworks can provide valuable information to designers early in the CAD flow. Next, we propose two sequential decision-making placement frameworks. An ML controller selectively chooses which optimization algorithms to run based on the unique properties of the circuit.

Results indicate that this dynamic placement approach is able to outperform static placement methods in both quality and runtime. Our final two approaches show how routing time can be reduced by first forecasting the congestion on each routing resource and then using it to initialize their costs within the routing algorithm. We first demonstrate how this can speed up routing using a traditional ML prediction model and then show that performance can be improved further on large circuits using a deep-learning image-to-image framework.