

Pyramid: Machine Learning Framework to Estimate the Optimal Timing and Resource Usage of a High-Level Synthesis Design

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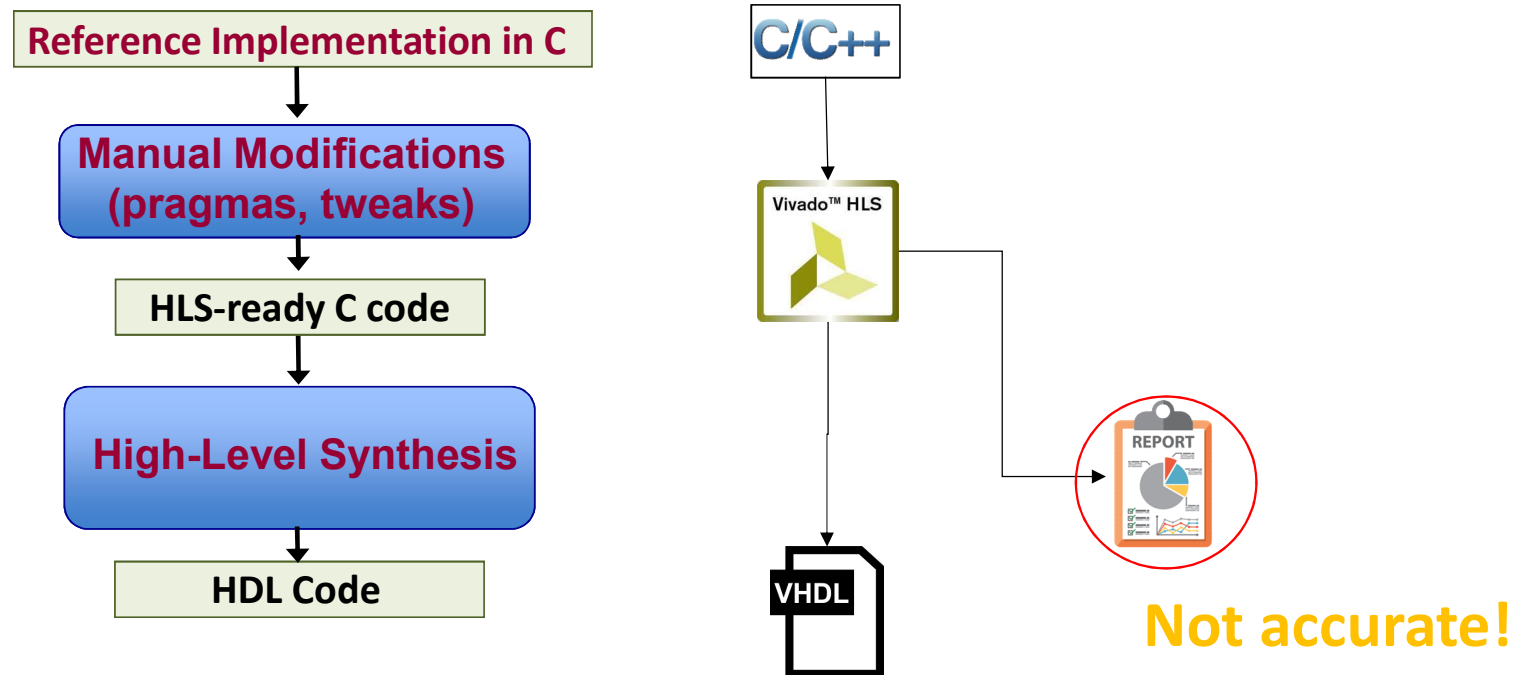
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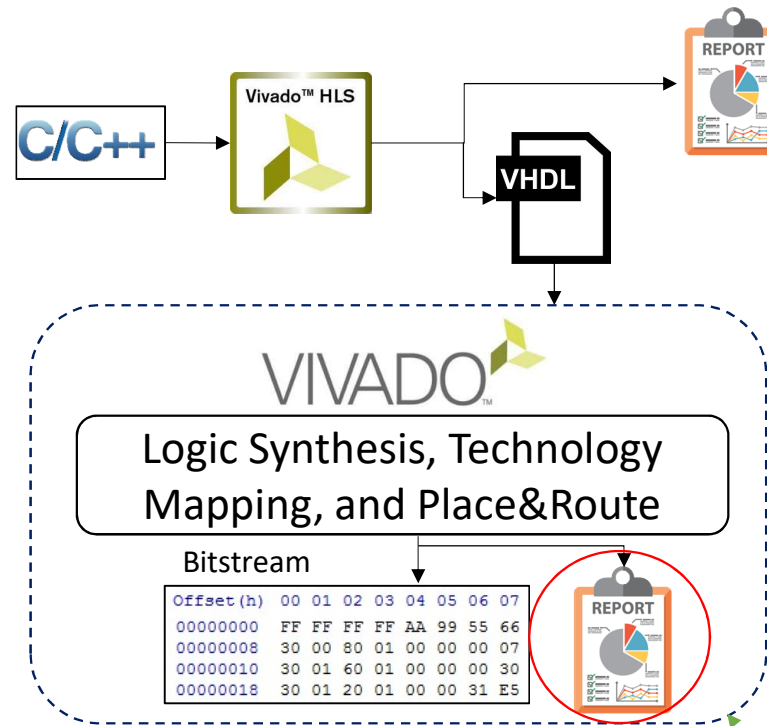
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HLS-Based Development and Benchmarking Flow

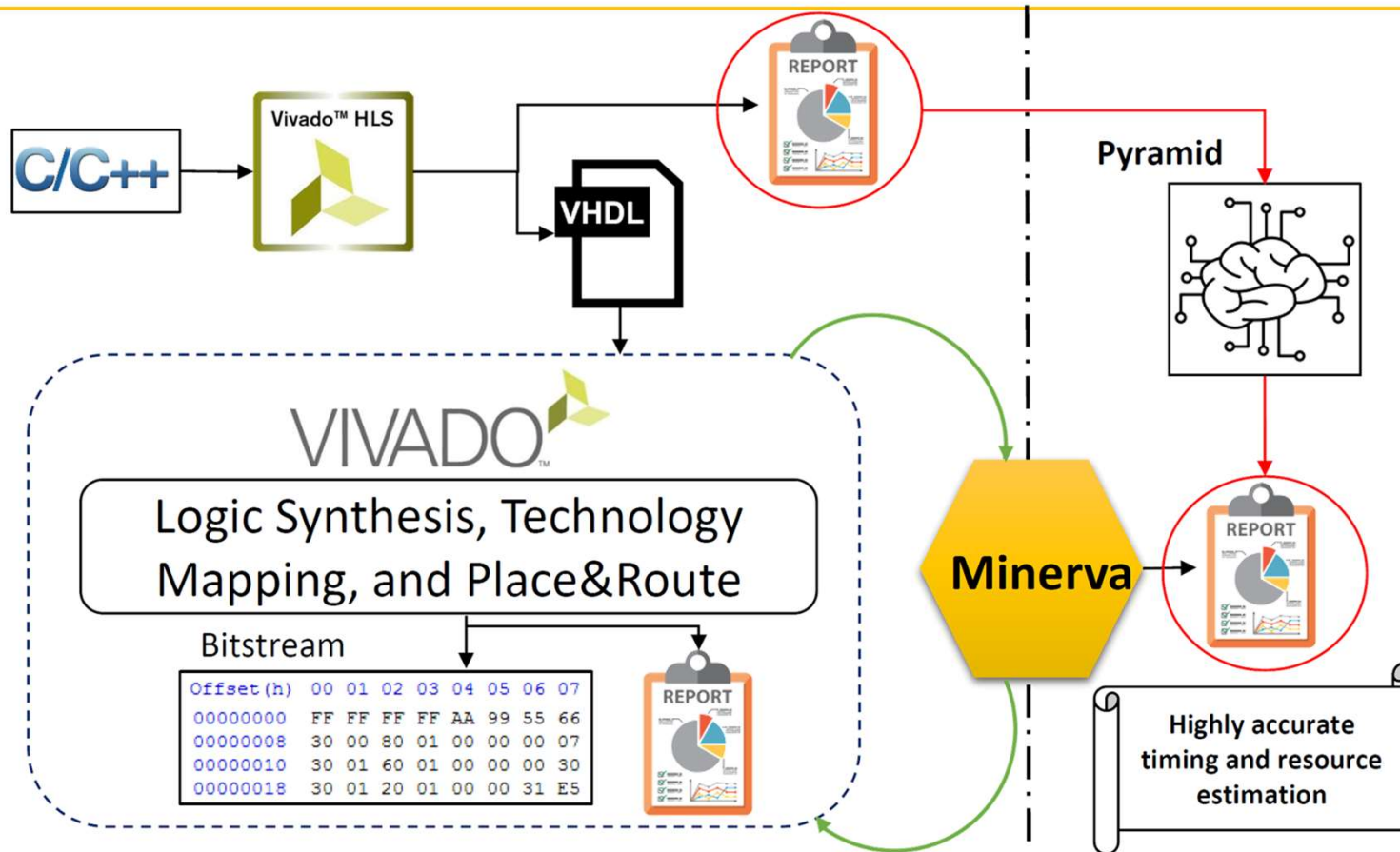


Static Timing Analysis using CAD Tools



Time consuming!
Not Optimal!

Solution



Goal of this Research

- We propose **Pyramid**, a framework that uses ML to accurately estimate the optimal performance and resource utilization of an HLS design
- For this purpose:
 - we first create a database of C-to- FPGA results from a diverse set of benchmarks using Minerva to find maximum clock frequency
 - We use the database to train an **ensemble** machine learning model to map the HLS-reported features to the results of Minerva

General ML Models

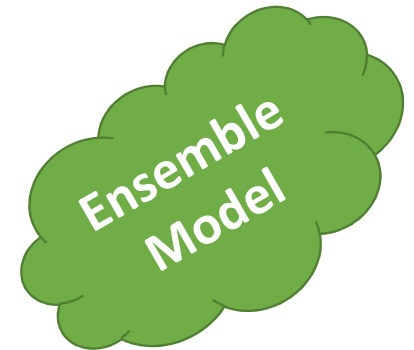
ML ESTIMATION ERRORS

Device		Artix7					Kintex7					Virtex7				
Resource		LUT	FF	DSP	BRAM	Timing	LUT	FF	DSP	BRAM	Timing	LUT	FF	DSP	BRAM	Timing
TP	LR	27%	19%	22%	29%	18%	23%	25%	17%	21%	20%	29%	20%	21%	19%	24%
	ANN	12%	17%	13%	14%	16%	10%	11%	19%	16%	15%	11%	14%	18%	14%	13%
	SVM	22%	16%	19%	18%	19%	20%	22%	18%	15%	17%	24%	21%	16%	17%	18%
	RF	9%	17%	19%	14%	16%	15%	18%	12%	11%	17%	16%	20%	19%	15%	14%

ML models: regression model, artificial neural network (ANN), support vector machine (SVM), and random forest (RF)

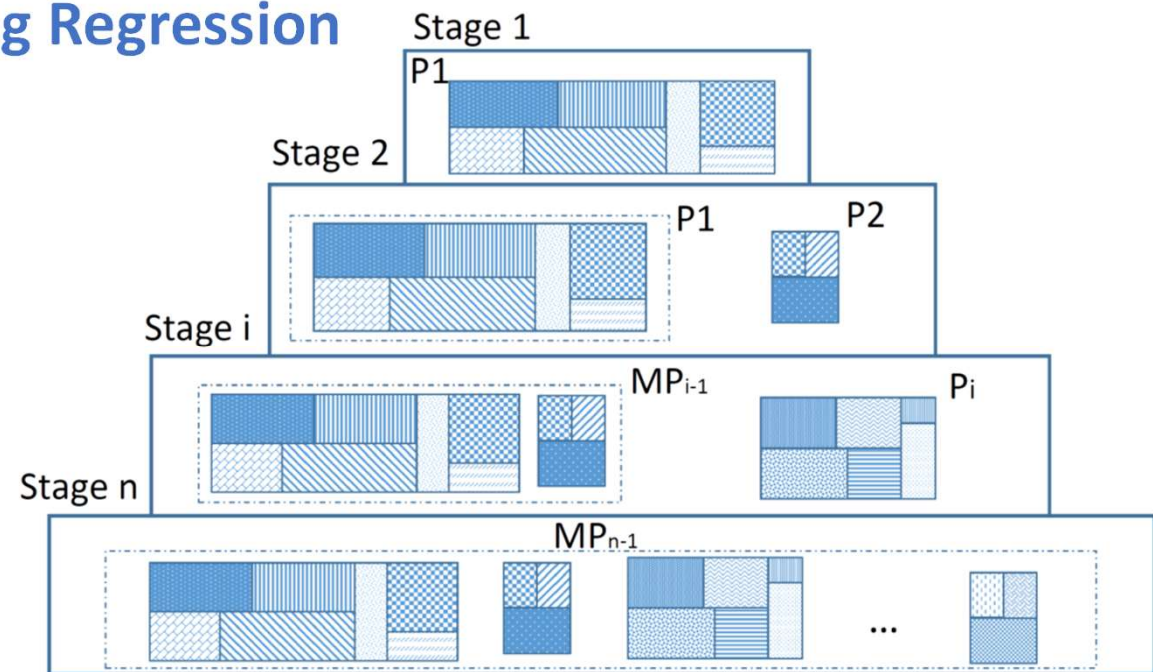
Tuning technique: Grid Search

Average Error: LR=23%, ANN=14%, SVM=19%, and RF=15%



Ensemble Model

Stacking Regression



Key Idea: Cross Validation and Batch Training

Model Parameters: threshold for the accuracy and the maximum number of iterations

Evaluation Results

AVERAGE ERROR OF PYRAMID ESTIMATIONS

Devices	Artix7		Kintex7		Virtex7	
Tragets	Resource	Timing	Resource	Timing	Resource	Timing
Pyramid-TP	6.3%	3.8%	5.2%	4.1%	4.9%	4.4%
Pyramid-TPA	4.8%	3.5%	4.7%	4.6%	4.8%	4.9%

AVERAGE ERROR OF ML TECHNIQUES FOR DIFFERENT BENCHMARKS

Benchmark's category	Machine Learning		Img/Vid Processing		Crypto.		Mathe.	
Targets	<i>Res</i>	<i>Tim</i>	<i>Res</i>	<i>Tim</i>	<i>Res</i>	<i>Tim</i>	<i>Res</i>	<i>Tim</i>
LR	29%	25%	17%	16%	38%	22%	11%	8%
ANN	17%	14%	13%	11%	19%	14%	8%	7%
SVM	22%	19%	18%	17%	23%	18%	10%	7%
RF	16%	16%	14%	12%	20%	15%	9%	7%
Ensemble	6%	5%	4%	3%	5%	4%	4%	3%

Questions

Thank you!



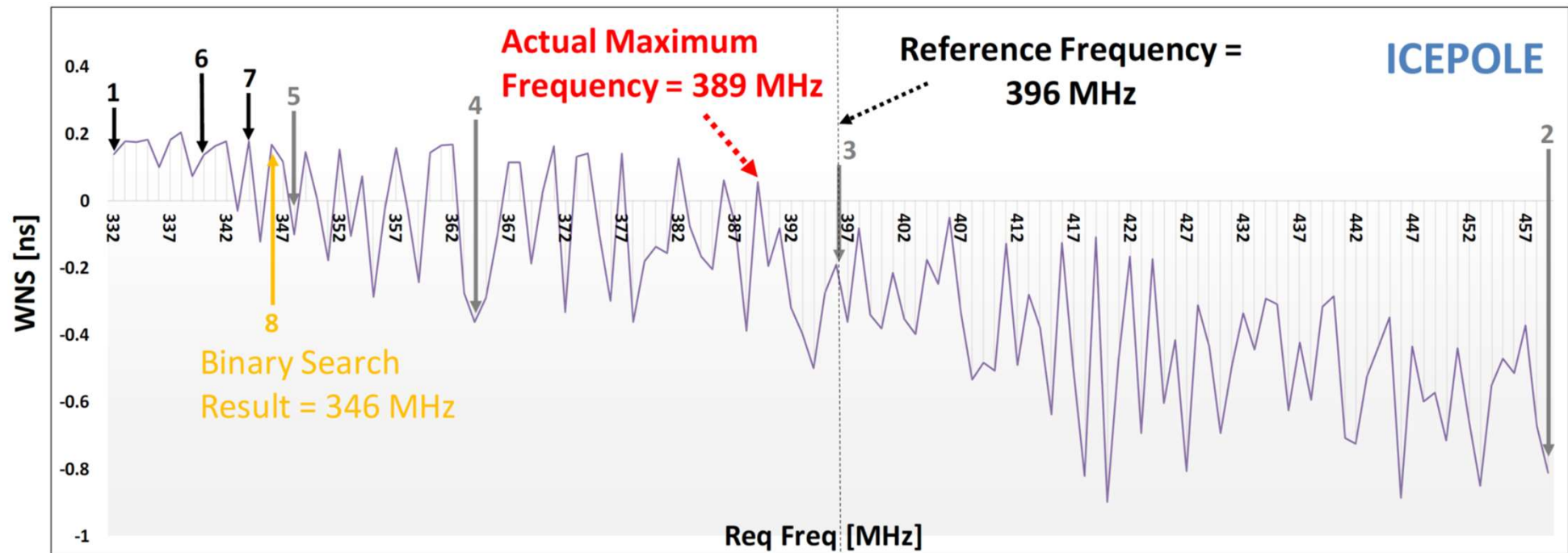
Supporting Slides

Inaccuracy of HLS Report

$$\text{Relative RMSE} = \sqrt{\frac{1}{N} \sum_{n=1}^N \left(\frac{p_i - a_i}{a_i} \right)^2} \times 100$$

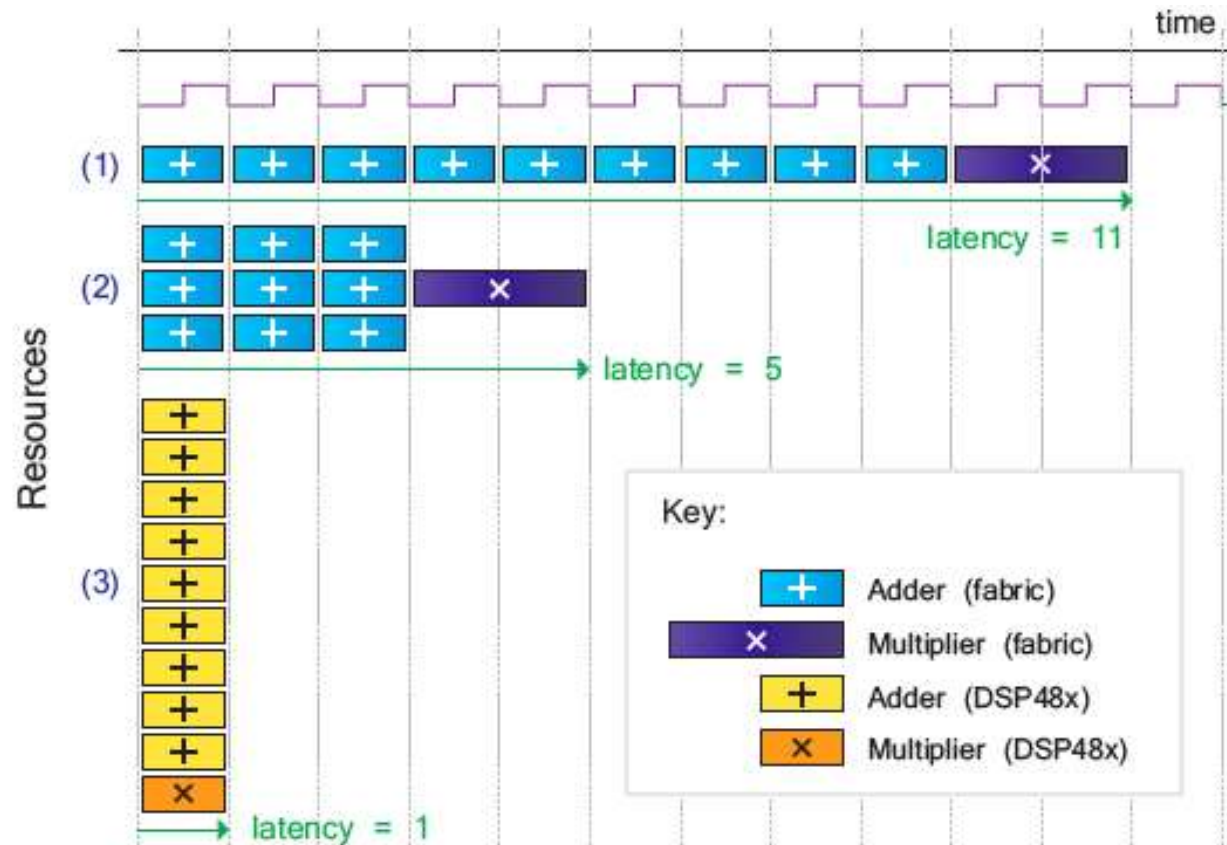
Devices	Artix7		Kintex7		Virtex7	
Tragets	Resource	Timing	Resource	Timing	Resource	Timing
HLS Estimate	91.7%	23.6%	112.5%	28.1%	88.4%	17.2%

Challenge of Hardware Evaluation

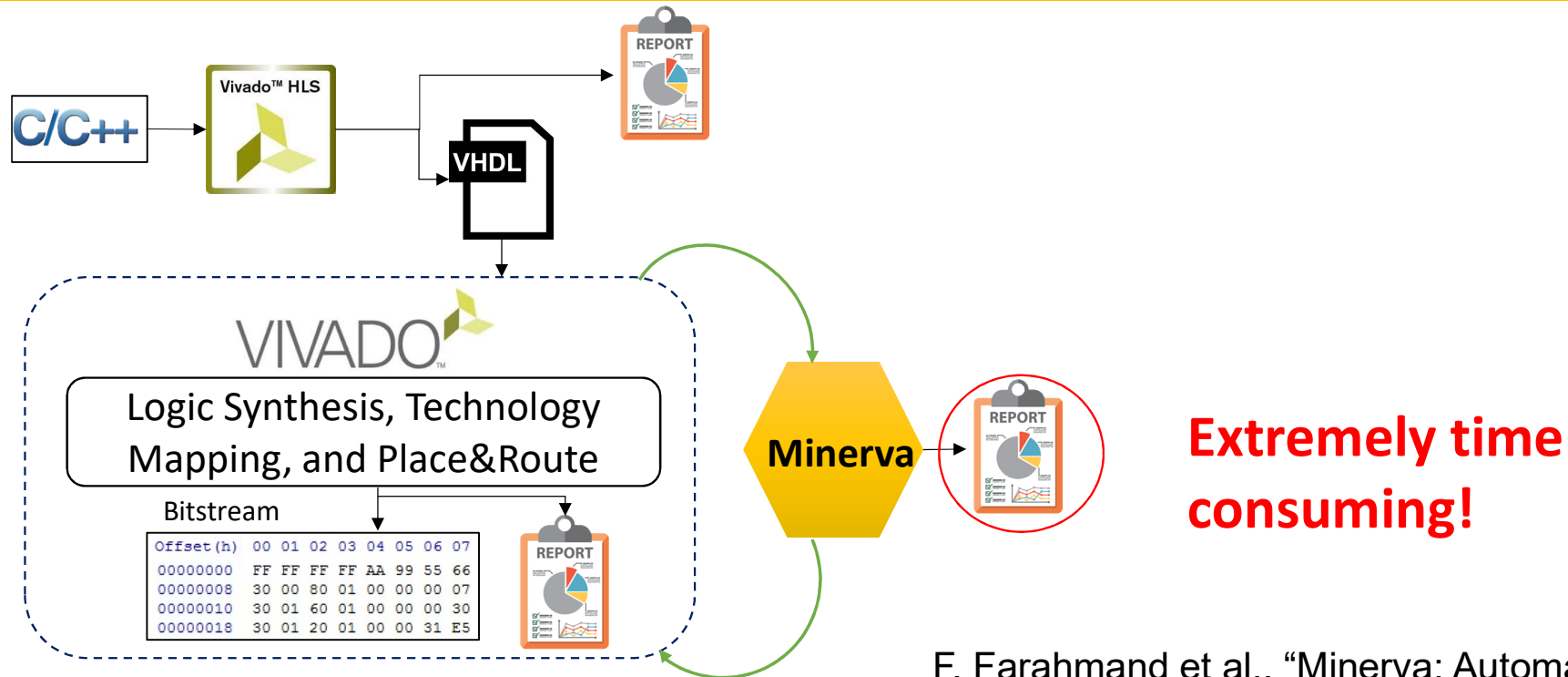


$$\text{Minimum Clock} = \text{Target Clock} - WNS$$

Impact of Optimization on the Outcome of HLS: Average of 10 numbers



Using Minerva to Tackle Finding Optimal Results



F. Farahmand et al., “Minerva: Automated hardware optimization tool,” in ReConFig, 2017.

Studied Applications

- Benchmarks: **Machsuit, S2CBench, CHStone, Rosetta, and xfOpenCV**
- Development suites:
Vivado and Vivado HLS version 2017.2
- Total number of applications: **90**
- Applications' types:
**Machine learning, Image/Video Processing
Cryptography, and Mathematical**

Data Collection

Feature Category	Brief Description	# features
Performance	Requested clock period, estimated clock period by HLS, Uncertainty	3
Resources	Utilization and availability of LUT, FF, DSP, and BRAM	36
Logic and arithmetic operation	Bitwidth/resource statistics of operations	29
Memory	Number of memory words/banks/bits;	2
Multiplexer	Multiplexer input size/bitwidth	2

- Total features: 72
- Data set: 60% for training, 20% for Validation, and 20% for testing (unseen data)