

# KOCL:

Kernel-level Power Estimation for Arbitrary  
FPGA-SoC-accelerated OpenCL Applications

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# Executive Summary

- *KAPow* for **OpenCL**
  - ‘K’ounting **Activity** for **Power** Estimation
- Hardware/software framework providing **kernel-level power estimates** for **OpenCL applications** running on **Altera FPGAs**
- Trains, adapts online with real workload
- Up to  $\pm 5\text{mW}$  accuracy
- Fully automated
- Minimalist API
- Open source
  - <https://github.com/PRiME-project/KOCL>

# Shameless Self Promotion

Introduced in  
IEEE D&T 34(6)

Self-Awareness in Systems on Chip 2017

## KOCL: Power Self-Awareness for Arbitrary FPGA-SoC-Accelerated OpenCL Applications

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*Editor's note:*  
Being aware of its own power consumption is essential for any system under power constraints, i.e. all systems with moderate or high complexity. This paper describes a tool that provides this power awareness for applications written in OpenCL, and implemented on FPGAs.  
—Axel Jantsch, TU Wien

host code. KOCL is an open-source, available online at <https://github.com/PRIME-project/KOCL>. To maximize accessibility, its use necessitates zero exposure to hardware.

Three major factors motivated us to develop KOCL, short for KAPow for OpenCL:

- the growing capabilities and popularity of high-level synthesis (HLS) tools for logic design,
- the desire to monitor subsystem power consumption without its direct measurement, and
- the benefits yielded through measurement and modeling at runtime.

SoCs consisting of multicore CPUs coupled with FPGAs are now commonplace. Their cost for low- to medium-volume applications makes them attractive for implementing systems featuring custom logic components. OpenCL is a software framework that enables developers to write applications targeting a range of heterogeneous platforms. In the context of FPGAs, it can be viewed as a means of specifying hardware systems at a high level of abstraction. *Kernel* functions, written in OpenCL's subset of C, are intended for

**■ GIVEN THE NEED** for developers to rapidly produce complex, high-performance, and energy-efficient hardware systems, methods facilitating their intelligent runtime management are of ever-increasing importance. For energy optimization, such control decisions require knowledge of power usage at subsystem granularity. This information must be made accessible to developers now accustomed to create systems from high-level descriptions, such as those written in OpenCL. To address these challenges, we introduce KOCL, a tool allowing OpenCL developers targeting FPGA-SoC devices to query live kernel-level power consumption using function calls embedded in their

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IEEE Design&Test

# Use Cases

- Hardware prototyping, design iteration
- Adaptive system deployment
  - Power-aware kernel selection
  - Fine-grained DVFS, clock gating, ...
- Fault, malware detection
- Billing
- ...

# KAPow

- Hardware/software framework providing **power breakdowns** for **arbitrary FPGA-based systems** at **user-specified granularity**

# KAPow

- Hardware/software framework providing **power breakdowns** for **arbitrary FPGA-based systems** at **user-specified granularity**
- Monitoring of switching activities
  - Power-indicative signals selected
- Online modelling
  - Compensates for changes in environment, workload
- System power measurements split by module

# KAPow: Further Reading

Introduced at  
IEEE FCCM'16  
(Best Paper)

2016 IEEE 24th Annual International Symposium on Field-Programmable Custom Computing Machines

## KAPow: A System Identification Approach to Online Per-module Power Estimation in FPGA Designs

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**Abstract**—In a modern FPGA system-on-chip design, it is often insufficient to simply assess the total power consumption of the entire circuit by design-time estimation or runtime power rail measurement. Instead, to make better runtime decisions, it is desirable to understand the power consumed by each individual module in the system. In this work, we combine board-level power measurements with register-level activity counting to build an online model that produces a breakdown of power consumption within the design. Online model refinement avoids the need for a time-consuming characterisation stage and also allows the model to track long-term changes to operating conditions. Our flow is named KAPow, a (loose) acronym for “*K*ounting Activity for Power estimation, which we show to be accurate, with per-module power estimates as close to  $\pm 5mW$  of true measurements, and to have low overheads. We also demonstrate an application example in which a per-module power breakdown can be used to determine an efficient mapping of tasks to modules and reduce system-wide power consumption by over 8%.

### 1. Introduction

In a world increasingly dominated by system-on-chip (SoC) designs, power efficiency is of ultimate concern due to the dark silicon effect: more transistors can be placed on a die than can be continuously switched. Designers put a large amount of effort into managing this challenge up-front, but many things can change once a system is manufactured and deployed: to simply assume worst-case behaviour incurs significant performance penalties under average conditions. For example, a system may be more produced where, due to variation, some modules are more power-efficient than others. An intelligent, self-aware system might independently control the power consumption of each module using dynamic frequency scaling. Tasks could then be mapped to these modules in a way that delivers the best overall performance given the constraints of the power budget, available hardware and work to be done.

Such runtime techniques would be particularly useful for FPGAs, where the shortened design cycles reduce the time available for offline analysis. FPGAs’ reconfigurable hardware makes it more difficult to implement well established techniques, such as power gating. Unfortunately, great opportunities for runtime adaptation. Unfortunately, the self-awareness necessary to deliver this vision is currently missing from the power consumption toolbox: we

can measure system-wide power consumption at runtime and forecast per-module contributions at design-time, but we cannot determine such a breakdown online.

### 1.1. Per-module Online Power Modelling

While power measurement at  $V_{DD}$  pins is common, manufacturing SoCs with per-module power domains is usually impractical due to increased metal and pad costs, particularly for a configurable technology such as the FPGA. A more feasible approach is to instead monitor the switch-more activity within each module, since switching is a key indicator of dynamic power. Models that forecast power consumption based on predicted switching activity are well established for use at design-time, however inaccuracies inevitably arise from assumptions made regarding data patterns and operating conditions. Some of these assumptions can be avoided by training a model during commissioning, but, unless the external conditions are static and alling, but, unless the system behaviour is captured by the training programme, such a model would be running blindly and errors will begin to accumulate. Instead, what is needed is a means to calculate a runtime power breakdown without relying on a stale model.

Figure 1 illustrates the benefits of an online, activity-based power model—described in this paper—used to estimate power consumption. The plot shows the error between

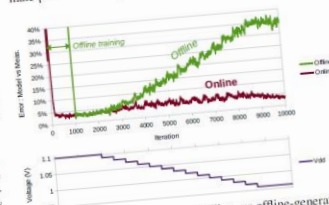


Figure 1: Error accumulations in online- vs offline-generated signal activity-to-power models under voltage scaling



# KAPow: Further Reading

Introduced at  
IEEE FCCM'16  
(Best Paper)

Extended in  
ACM TRETs  
11(1)

**KAPow: High-Accuracy, Low-Overhead Online Per-Module Power Estimation for FPGA Designs**

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PETER Y. K. CHEUNG, and GEORGE A. CONSTANTINIDES, Imperial College London

In an FPGA system-on-chip design, it is often insufficient to merely assess the power consumption of the entire circuit by compile-time estimation or runtime power measurement. Instead, to make better decisions, one must understand the power consumed by each module in the system. In this work, we combine measurements of register-level switching activity and system-level power to build an adaptive online model that produces live breakdowns of power consumption within the design. Online model refinement avoids time-consuming characterization while also allowing the model to track long-term operating condition changes. Central to our method is an automated flow that selects signals predicted to be indicative of high power consumption, instrumenting them for monitoring. We named this technique KAPow, for 'K'ounting Activity for Power marks. We also propose a strategy allowing for the identification and subsequent elimination of counters found to be of low significance at runtime, reducing algorithmic complexity without sacrificing significant accuracy. Finally, we demonstrate an application example in which a module-level power breakdown can be used to determine an efficient mapping of tasks to modules and reduce system-wide power consumption by up to 7%.

**CCS Concepts:** • Computing methodologies → Learning linear models; Modeling methodologies; • Hardware → Design modules and hierarchy; Reconfigurable logic and FPGAs; System on a chip; On-chip resource management; On-chip sensors; Power estimation and optimization;

**Additional Key Words and Phrases:** Fine-grained power estimation, online modeling, power-aware scheduling

**ACM Reference format:**  
James J. Davis, Eddie Hung, Joshua M. Levine, Edward A. Stott, Peter Y. K. Cheung, and George A. Constantinides. 2017. KAPow: High-Accuracy, Low-Overhead Online Per-Module Power Estimation for FPGA Designs. *ACM Trans. Reconfigurable Technol. Syst.* 11, 1, Article 2 (January 2018), 22 pages. <https://doi.org/10.1145/3129789>

**1 INTRODUCTION**

In a world increasingly dominated by systems-on-chip (SoCs), power efficiency is of ultimate concern due to the dark silicon effect (Esmailzadeh et al. 2011): more transistors can be placed on a

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**PRiME**  
<http://www.prime-project.org>

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# Motivation

- Have existing fine-grained power estimation framework...
- ... but it requires HDL expertise
- “Hardware is hard” – can we hide it?

# Motivation

- Have existing fine-grained power estimation framework...
- ... but it requires HDL expertise
- “Hardware is hard” – can we hide it?
- Aims:
  - Generality
  - Minimal user effort
  - Transparency
  - Low overheads

# OpenCL for FPGAs

- Adopted as input language by Altera, Xilinx
- Front-ends to existing vendor tools
  - High-level synthesis
  - System integration
  - Mapping, placement, routing, ...
- Kernel code compiled offline...
  - 1 kernel = 1 hardware accelerator
- ... and stitched to supporting infrastructure
  - Global memory interfacing
  - Launching kernels

# Developer Burden: Hardware

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- Before:

```
./aoc <.cl file> --board <board name>
```

- After:

```
./koc <.cl file> --board <board name>
```

# Developer Burden: Hardware

- Before:

```
./aoc <.cl file> --board <board name>
```

- After:

```
./koc <.cl file> --board <board name>
```

- Optional flags:

– kernels

Choose a subset of kernels to monitor

– kapow\_n

– kapow\_w

} Control fidelity of measurements

# Developer Burden: Software

- Initialise:

```
#include "KOCL.h"
KOCL_init(float <update period>);
```

- Controls reactivity of power model

- Use:

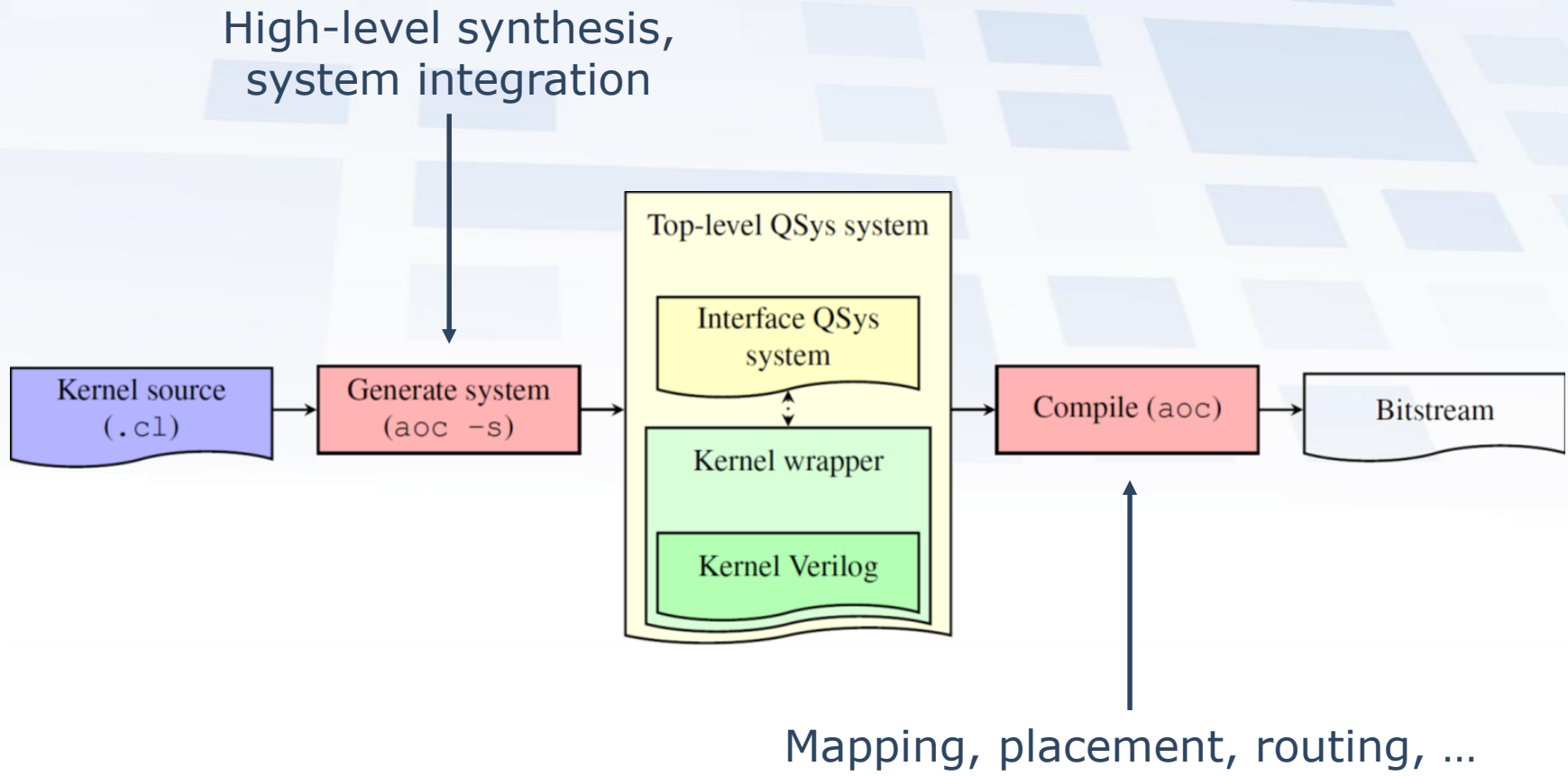
```
KOCL_built();
KOCL_get(char* <kernel name>);
KOCL_get("static");
```

- Clean up:

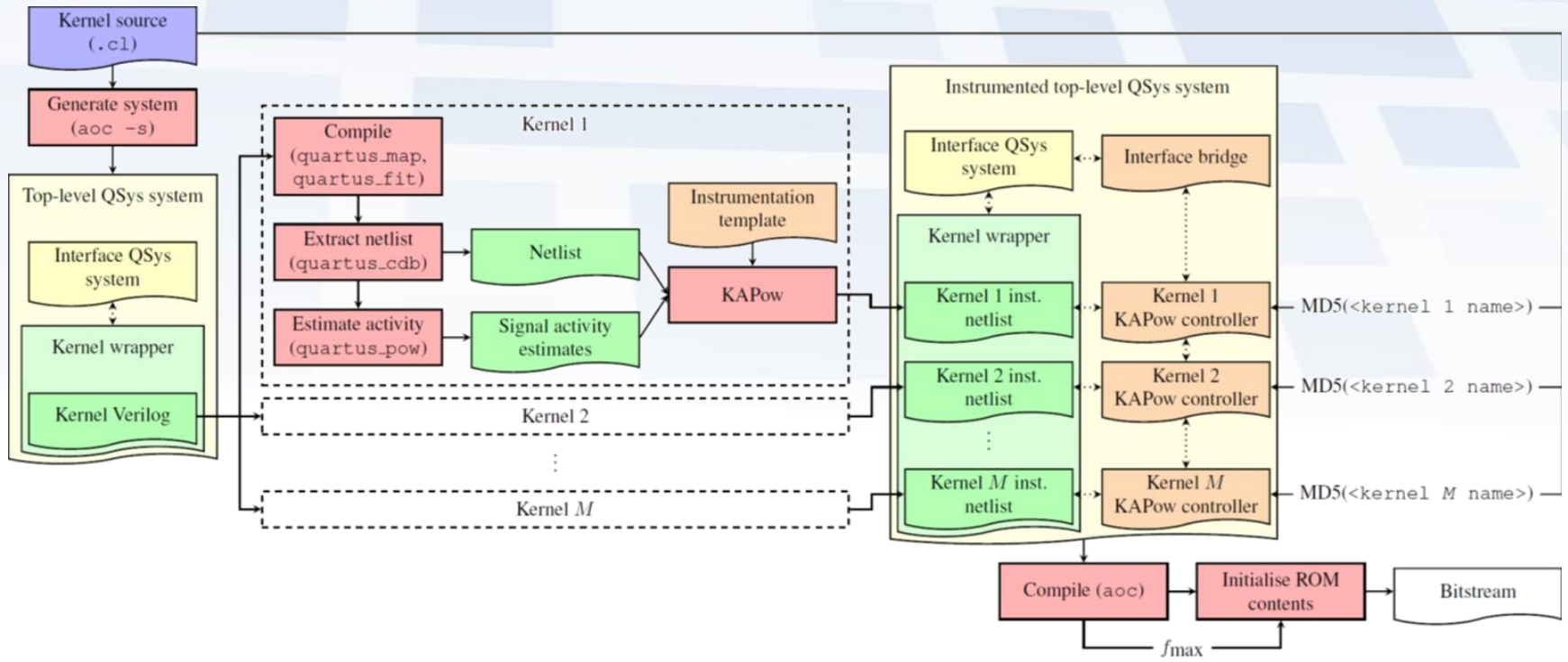
```
KOCL_del();
```



# Vanilla Tool Flow

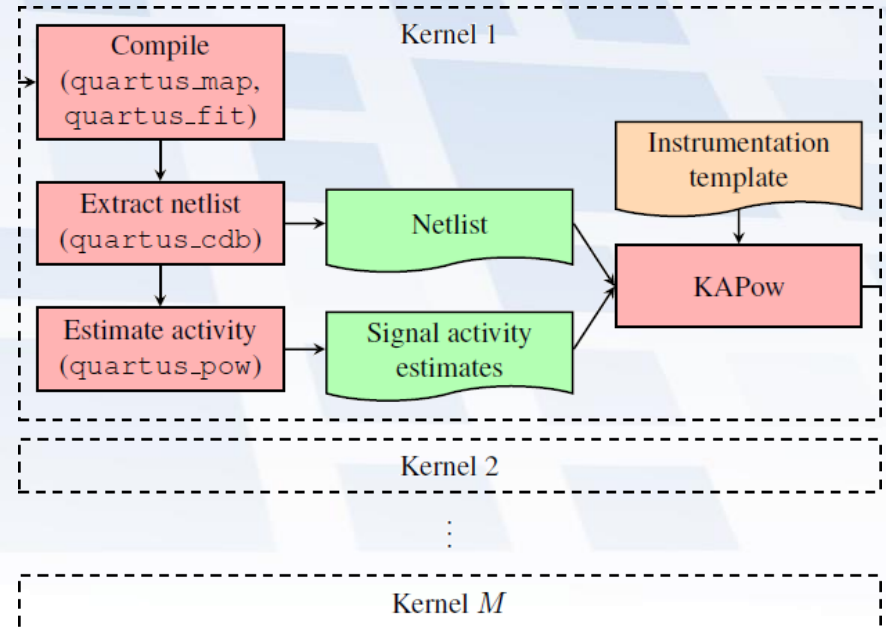


# KOCL Tool Flow



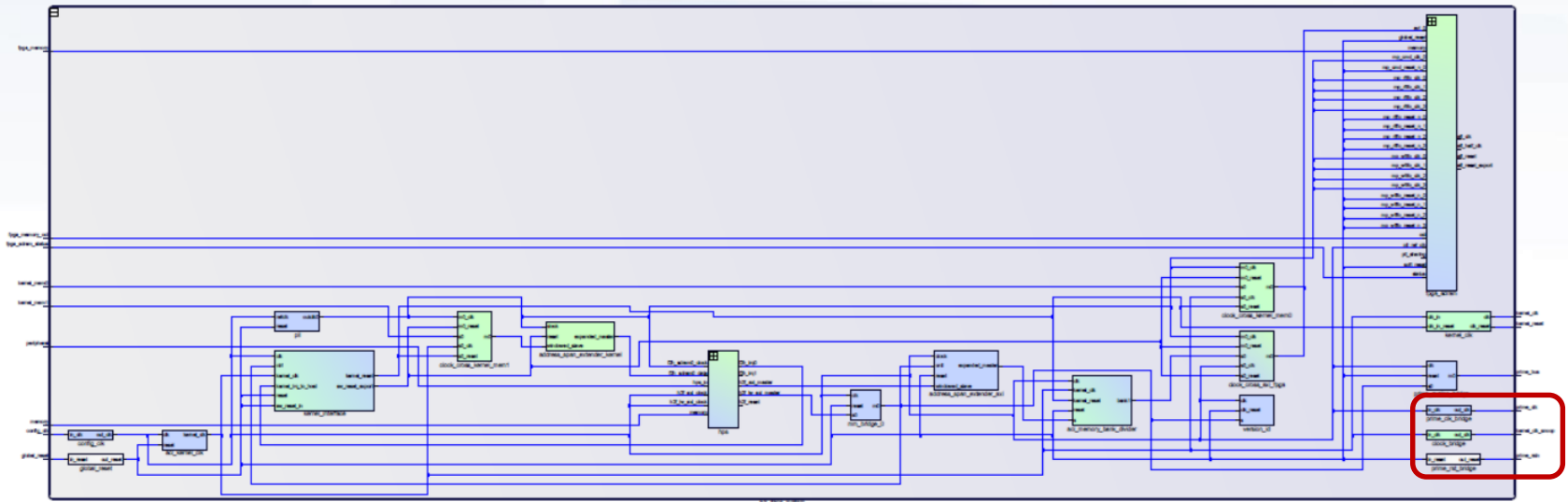
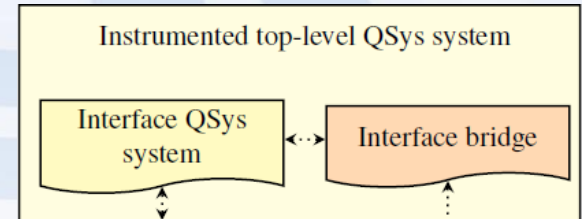
# KOCL Tool Flow: HDL

- Per kernel:
  - Compile → netlist
    - Specifies use of FPGA resources
  - Perform power simulation to obtain switching estimates
    - Fast
    - No user input
  - Augment  $N$  most-switching signals with  $W$ -bit activity counters
  - Substitute for original HDL



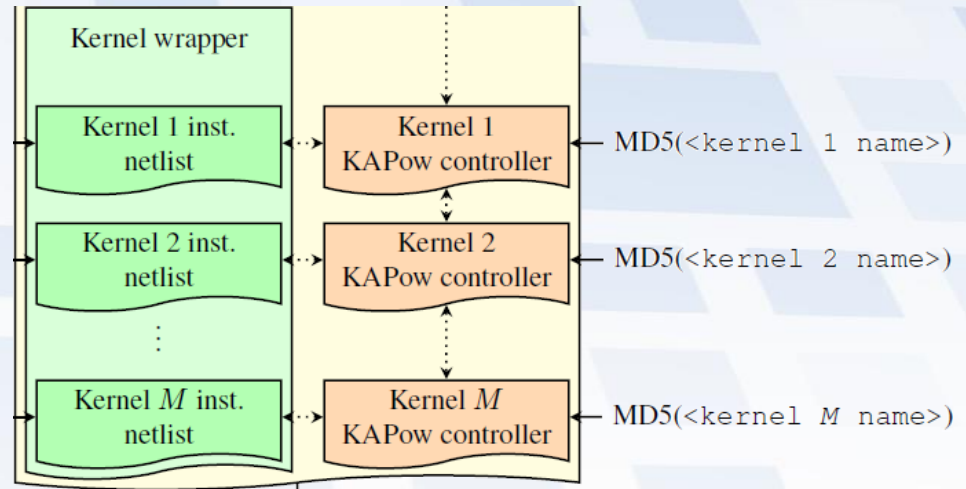
# KOCL Tool Flow: Interfacing 1

- Expose busses to allow counter control, readback



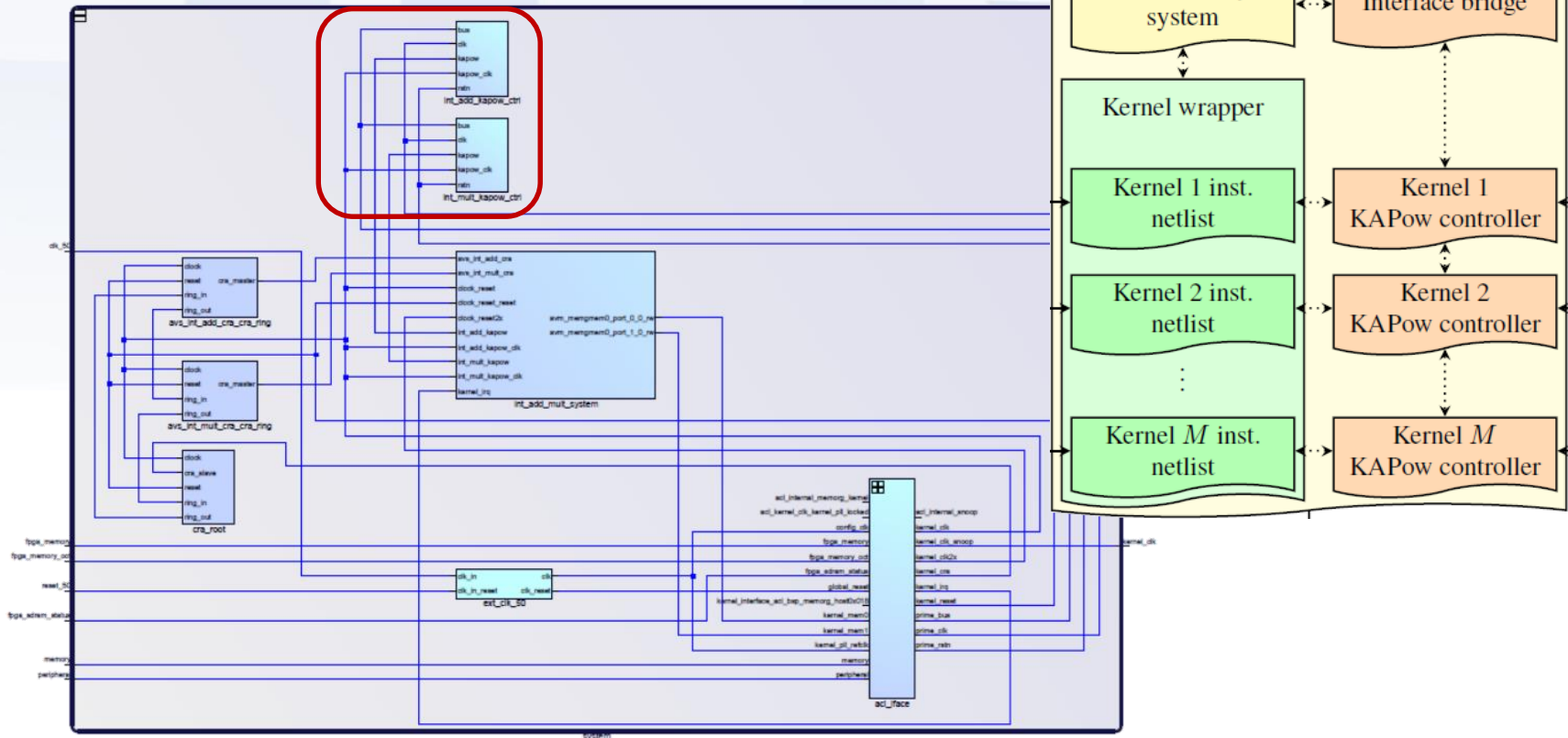
# KOCL Tool Flow: Control

- Per kernel:
  - Add controller
  - Connect to counters in netlist
  - Parameterise with hash of kernel's name



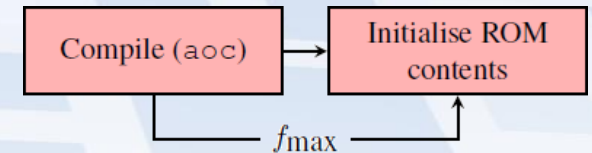
# KOCL Tool Flow: Interfacing 2

- Connect controllers



# KOCL Tool Flow: TTL

- Need to determine optimal measurement period
  - Too small: low dynamic range
  - Too large: potential overflow
- Read  $f_{\max}$  from compilation report
- Given  $f_{\max}$ ,  $W$ , calculate TTL
- Apply via controller ROMs





# KOCL Software

- Launched by, runs alongside host code
- Python w/Numpy, C API

# KOCL Software

- Launched by, runs alongside host code
- Python w/Numpy, C API
- Three threads:
  - **Model**
    - Talks to hardware
    - Performs power modelling
  - Interface
    - Responds to host code requests
  - Messenger
    - Model-interface communication

# KOCL Software: Model

- Initialisation:
  - Establish kernel names from bitstream
  - Discover controllers in hardware
  - Match to kernel names using hashes
  - Read parameters ( $N$ ,  $W$ ) from controllers
  - Construct model

# KOCL Software: Model

- Initialisation:
  - Establish kernel names from bitstream
  - Discover controllers in hardware
  - Match to kernel names using hashes
  - Read parameters ( $N$ ,  $W$ ) from controllers
  - Construct model
  
- Every `update_period`:
  - Get activity, system power measurements
  - Update model
  - Pass power breakdown to messenger

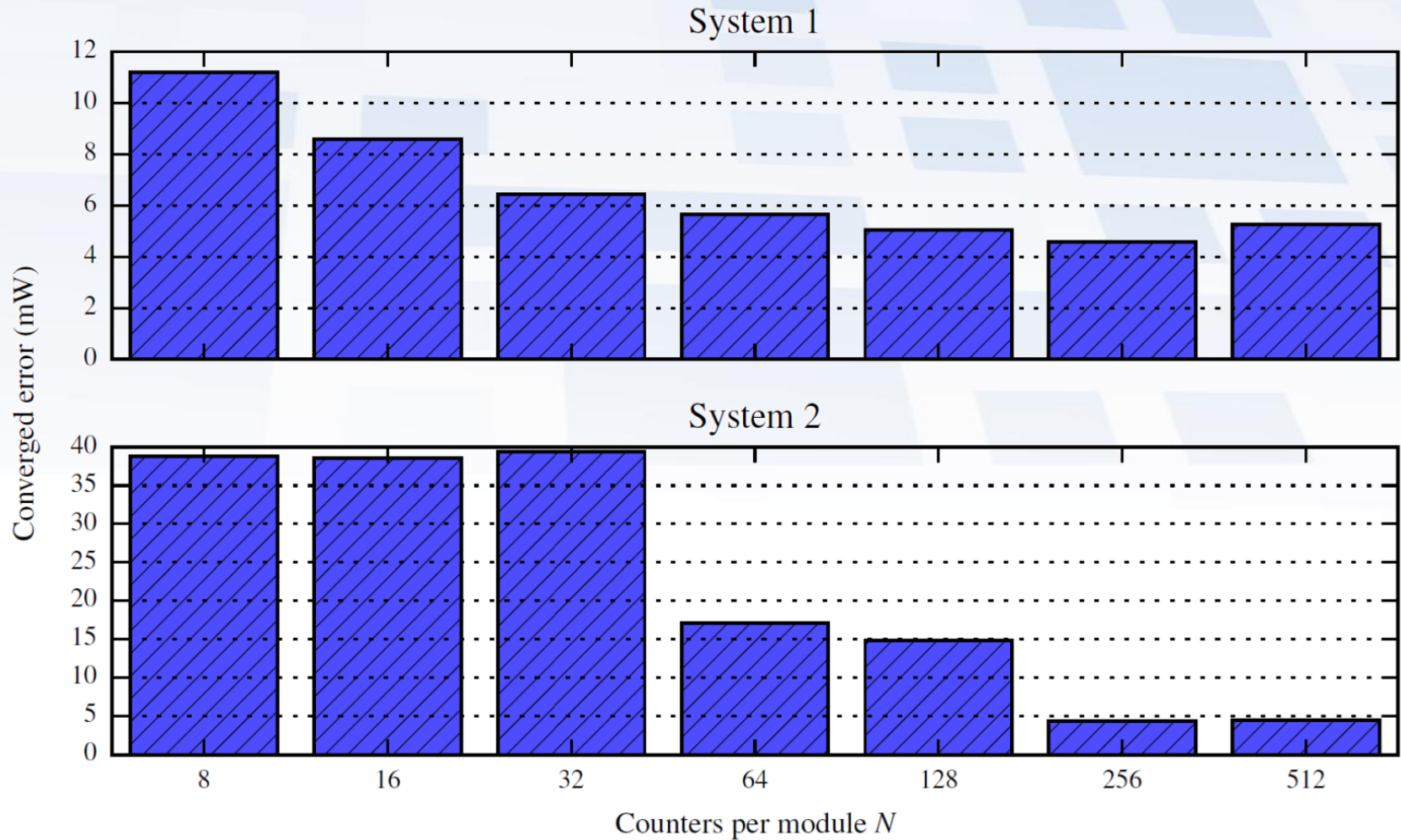
# Results

- Things of interest:
  - **Accuracy**
    - Estimate vs measurement
  - Compilation time overhead
  - Area overhead
  - Power overhead
  - Max. model update rate

# Results

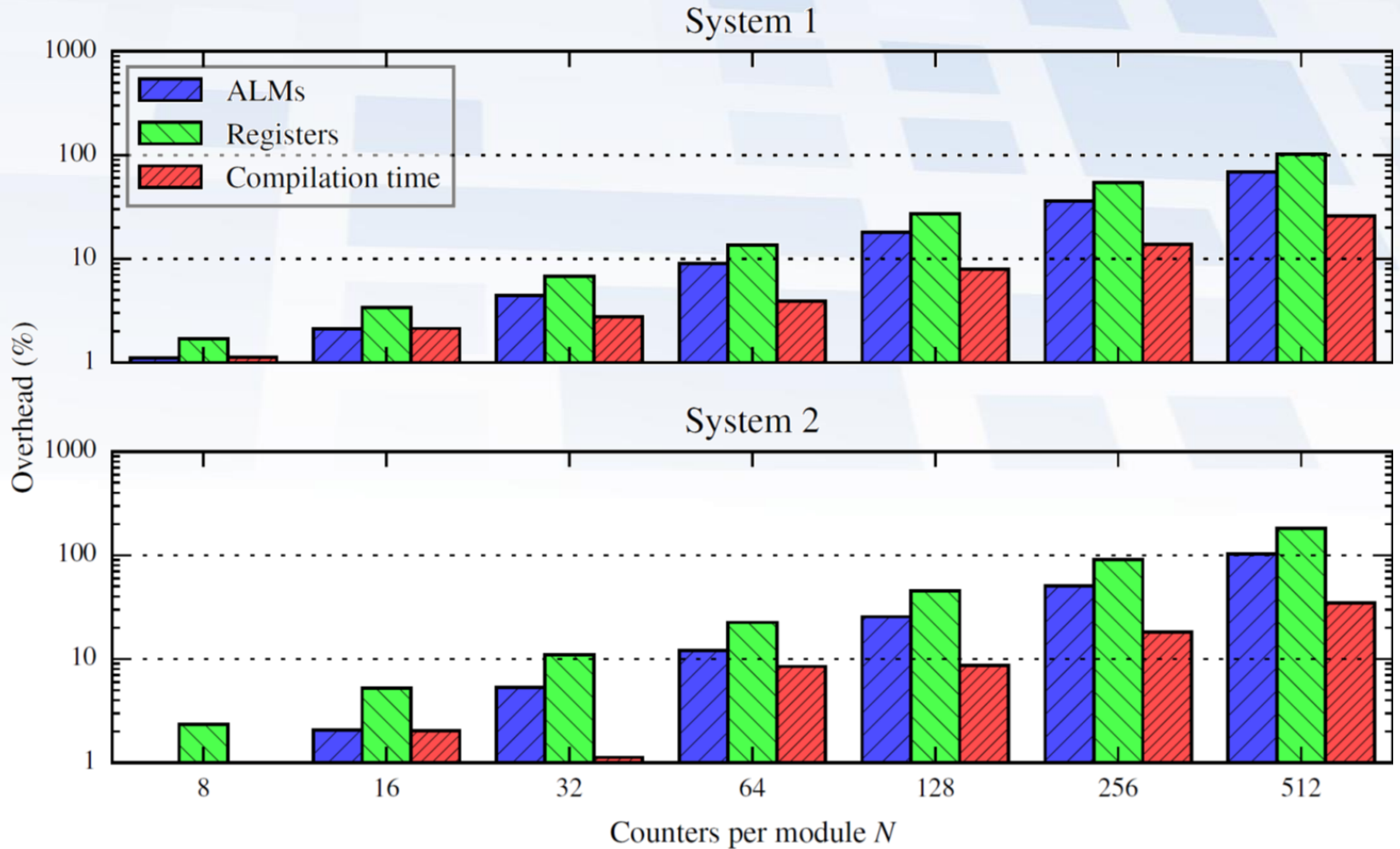
- Things of interest:
  - **Accuracy**
    - Estimate vs measurement
  - Compilation time overhead
  - Area overhead
  - Power overhead
  - Max. model update rate
- Particularly dependent on choice of  $N$
- Found  $W = 9$  generally best accuracy-overhead compromise

# Accuracy



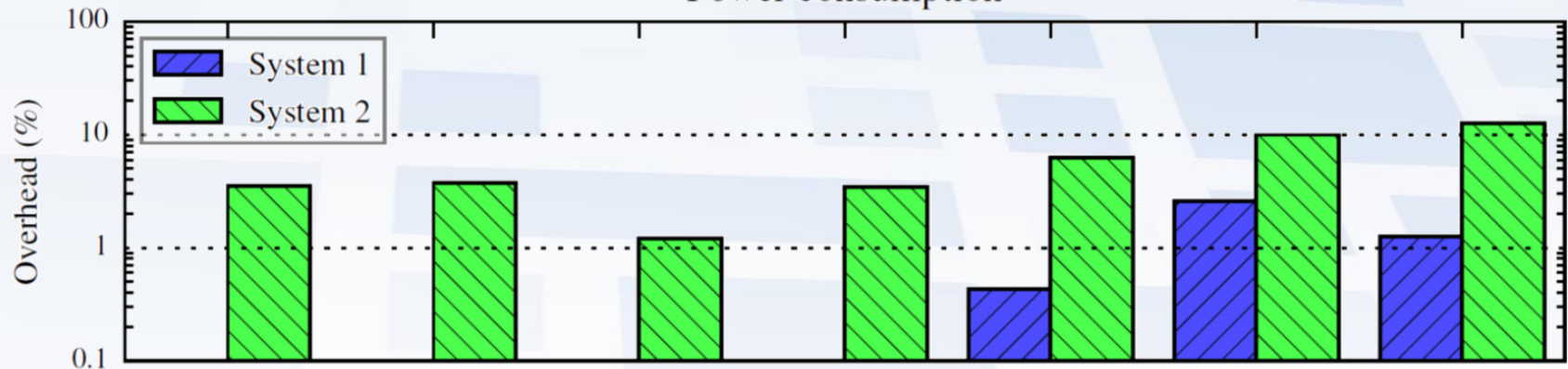


# Compilation Overheads

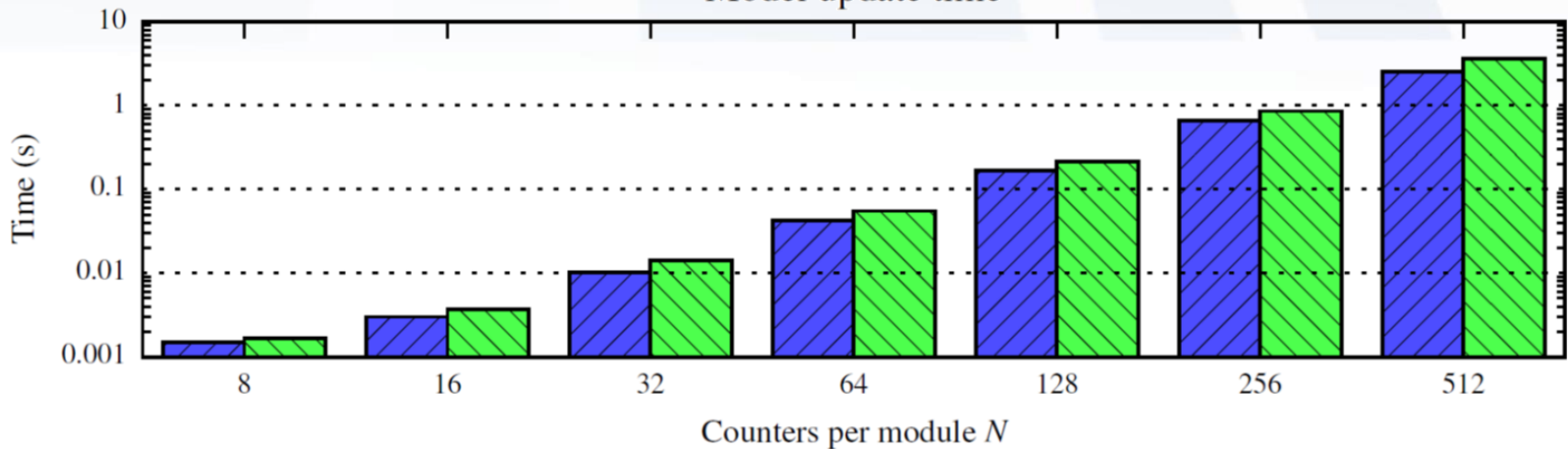


# Runtime Overheads

Power consumption



Model update time



# Further Work

- Improved signal selection
- Incorporation of macro modelling
- Use for system-level control
- More devices, vendors
- Similar tools for monitoring performance, reliability

# Preliminary Improvements

Signal selection  
improved in  
FPL'17

## STRiPE: Signal Selection for Runtime Power Estimation

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**Abstract**—Knowledge of power consumption at a subsystem level can facilitate adaptive energy-saving techniques such as power gating, runtime task mapping and dynamic voltage and/or frequency scaling. While we have the ability to attribute power to an arbitrary hardware system's modules in real time, the selection of the particular signals to monitor for the purpose of power estimation within any given module has yet to be treated as a primary concern. In this paper, we show how the automatic analysis of circuit structure and behaviour inferred through vectored simulation can be used to produce high-quality rankings of signals' importance, with the resulting selections able to achieve lower power estimation error than those of prior work coupled with decreases in area, power and modelling complexity. In particular, by monitoring just eight signals per module (1–0.3% of the total) across the 15 we examined, we demonstrate how to achieve runtime module-level estimation errors 1.5–6.9× lower than when reliant on the signal selections made in accordance with a more straightforward, previously published metric.

### I. INTRODUCTION

The power behaviour of bus-based, modular hardware systems, including those implemented on FPGAs, at subsystem granularities is of ever-increasing concern as user expectations for simultaneous performance and energy efficiency improvements rise. Information about such behaviour can be used to inform runtime decision-making, allowing, for example, tasks to be power-efficiently mapped to the hardware upon which they execute. In our previous work [1], we showed how module-level power breakdowns could facilitate power savings of up to 8%. Otherwise, variation at commissioning or degradation thereafter, behave differently at runtime; always assuming worst-case conditions leads to suboptimal performance and efficiency. Since the facilitation of separate power islands for module-level power measurement is usually impractical, a proxy—in particular, switching activity—must be used to estimate modules' power contributions via a model.

Given fixed overhead budgets, we are faced with the problem of selecting which signals to monitor in order to maximise the quality of a system power breakdown. Since, as shown by our results, monitoring overheads are proportional to the number of signals selected and, in the absence of model overfitting, the quality of the power estimate will improve monotonically with each additional signal monitored, we can cast this challenge within an optimisation setting: select the  $N$  signals likely to provide the best-quality power estimate, for any  $N$ , for each of the modules a system is composed of.

Figure 1 contrasts results obtained for this paper with those obtained in our prior work [1], the state-of-the-art power estimation framework from which we use for instrumentation

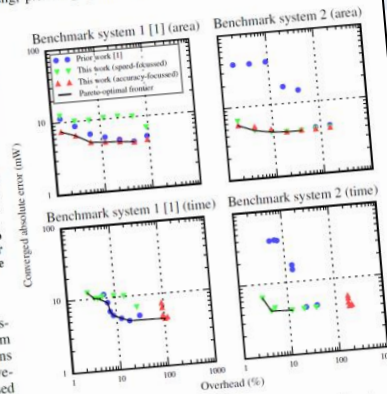


Fig. 1. Scatter plots of area and compilation time overheads vs achieved power estimation error for two benchmark systems using signal selection methods from our prior work [1] and those herein. The proposed selection methods are described in Sections III-A and III-B, the latter with  $T = 1000$ , while the benchmark systems are those in Sections V-A and V-B. The experiments described are described in Section VI. Overhead results are normalised to those for the equivalent system lacking runtime power estimation capability.

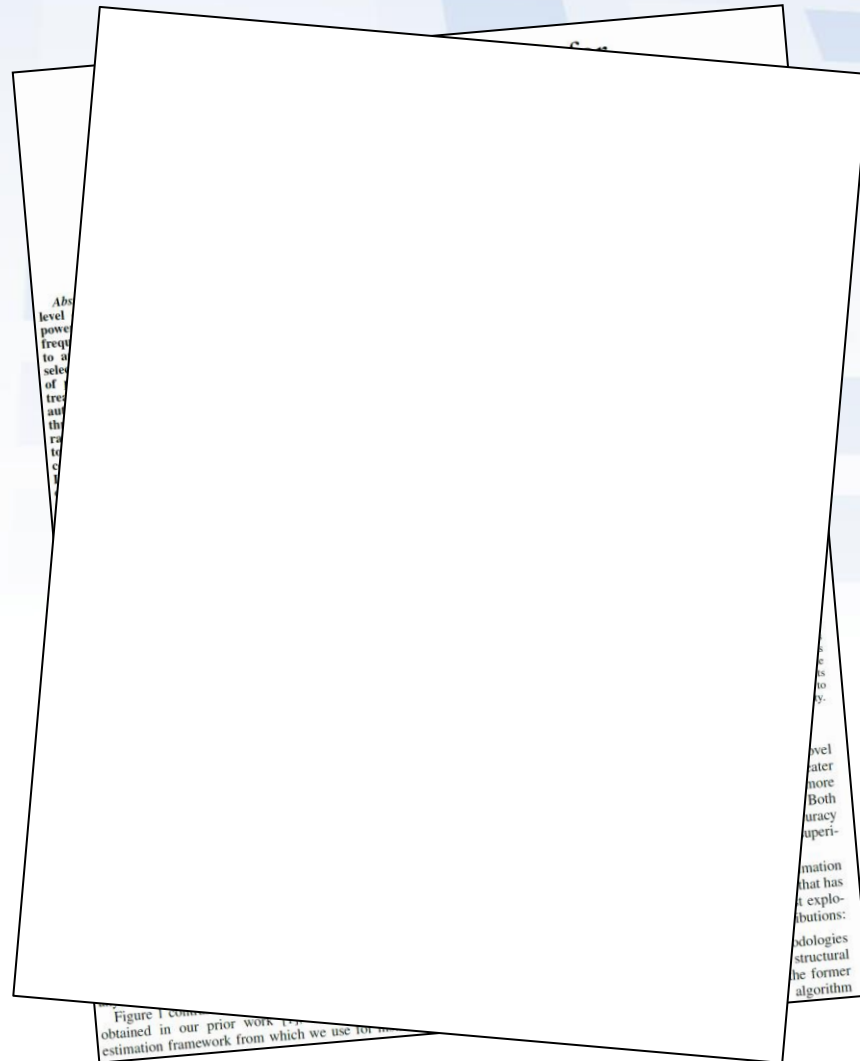
and modelling. The plots' frontiers highlight that the two novel signal selection techniques we propose can achieve greater signal accuracy for lower overheads than when relying upon the more simplistic equivalent currently found in the literature. Both show generality while the speed (Section III-A) and accuracy (III-B)-focussed methods demonstrate their respective superiorities over that used in our previous work.

The automatic signal selection for runtime power estimation (or STRiPE) of arbitrary hardware systems is a subject that has not been comprehensively studied. We present its first exploration in this paper, making the following novel contributions:

- We propose two new signal selection methodologies based on the automated analysis of modules' structural and statistical properties at compilation time, the former based on a fast graph centrality-computing algorithm

# Preliminary Improvements

Signal selection  
improved in  
FPL'17



Extension  
in the works...

# Summary

- Framework providing **kernel-level power estimates** of **arbitrary OpenCL systems** executing on **Altera FPGAs** to **host code**
- Easy to use
  - No hardware exposure
- $\geq$  order-of-magnitude accuracy improvement vs simulation
- Remains under active development

# Summary

- Framework providing **kernel-level power estimates** of **arbitrary OpenCL systems** executing on **Altera FPGAs** to **host code**
- Easy to use
  - No hardware exposure
- $\geq$  order-of-magnitude accuracy improvement vs simulation
- Remains under active development
  
- Open source
  - <https://github.com/PRiME-project/KOCL>
  - Plug-and-play Linux image, demo apps included
- Please use and provide feedback!

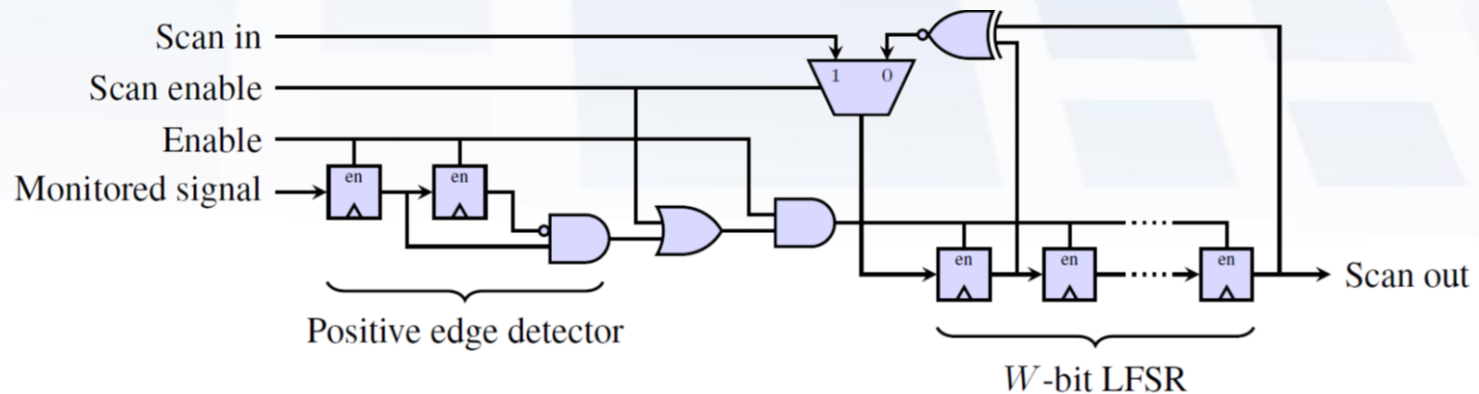




# Backup

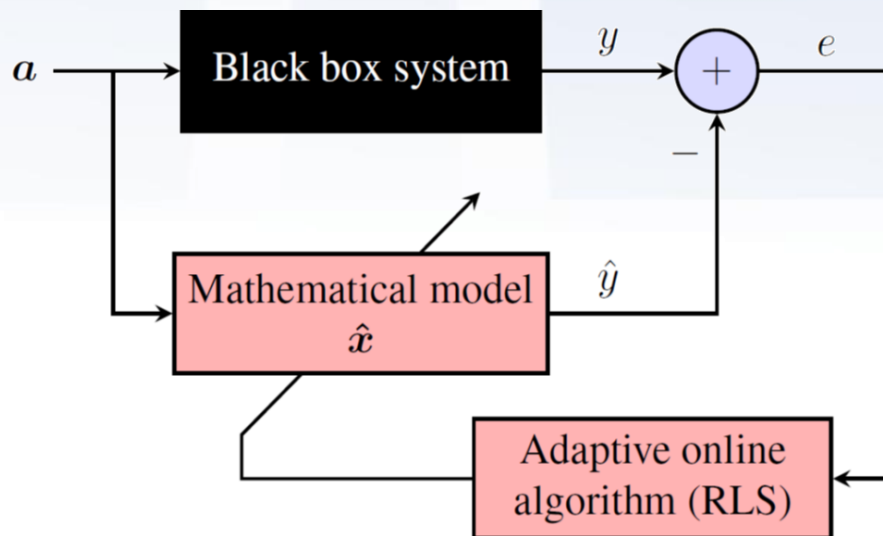
# KAPow: Monitoring

- Modules analysed to identify power-indicative signals
- Lightweight activity counters transparently inserted



# KAPow: Modelling

- Activities + system power  $\rightarrow$  module-level power
- Online training, refinement
  - Adapts to changes in voltage, temperature, workload, noise, ...



$a$ : activity counts  
 $y$ : measured power  
 $\hat{y}$ : estimated power  
 $e$ : error  
 $\hat{x}$ : model coefficients