

6/27/15

SAND2015-5175C

# Phase Detection with Hidden Markov Models for DVFS on Many-Core Processors

**Joshua Dennis Booth**

Computer Science Research Institute,  
Sandia National Laboratories



*Exceptional  
service  
in the  
national  
interest*



Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000. SAND NO. 2014-XXXX

# Acknowledgement

## Coauthors

- Jagadish Kotra, jbk5155@cse.psu.edu  
Ph.D. Candidate CSE, Penn State
- Hui Zhao, hzz105@cse.psu.edu  
Ph.D. CSE, Penn State
- Mahmut Kandemir, kandemir@cse.psu.edu  
Professor CSE, Penn State
- Padma Raghavan, raghavan@cse.psu.edu  
Distinguished Professor CSE, Penn State

## Funding Support

- NSF Grants 1213052, 1205618, 1439021, 096389, 1017882
- Grant support from Intel

## Disclaimer

The views presented here are the author's only.

Sandia National Lab takes no responsibility for this work or results.

## Motivation, Current Problem

- Current DVFS Techniques

- Phases and Hidden Markov Models

## Proposed Approach

- Phased-Based DVFS, *PVFS*

- Initialization

- Training

- Applying

## Experimental Results

- Setup

- Observed HMMs

- Major Results

## Motivation, Current Problem

Current DVFS Techniques

Phases and Hidden Markov Models

## Proposed Approach

Phased-Based DVFS, *PVFS*

Initialization

Training

Applying

## Experimental Results

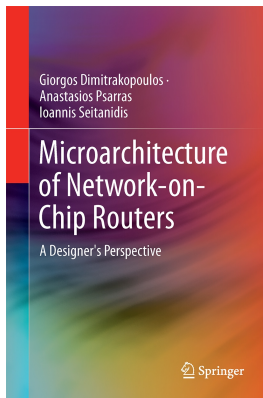
Setup

Observed HMMs

Major Results



*Future Intel Many-Core, 60+ cores, 300W+*



*NoC, SoC etc*



*GPU, 2496+ Cuda cores, 240W+*

- Coding styles and techniques vary greatly with device
- The execution pattern (time, hardware components used, power) vary for same code.

# DVFS Techniques

## Goals

- Detecting if code has area with poor performance
- Identifying code segments for optimize  
Characterizing interaction with hardware leading to performance, power, and scalability.
- Value of time investment

## Current Techniques

- Time-Driven
  - Samples taken at regular interval
  - Can be applied to a multitude of device components
  - Can it scale ?
- Compiler-Driven
  - Critical path analysis
  - Hard problem, Integer Linear Programming
  - What about applications that vary greatly with input?

## Can We Do Better?

## Phase

- All goals can be reworded in terms of *Phase*
- *Phase*: a segment of an application characterized with a unique performance and power
- Even short applications have multiple phases
- Long running HPC application having many!
- Phase detection is difficult

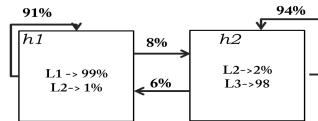
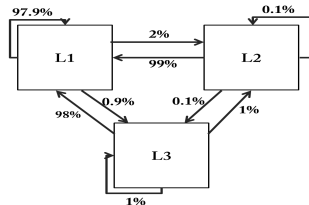
## Statistical Models

- Have been shown to be able to identify Phase
- Many different statistical models and levels of depth that can be taken
- Need a model that can discover interaction of measurable observations

# Hidden Markov Models for Phase Detection

## Hidden Markov Models (HMMs)

- A form of Dynamic Bayesian Network
- Model time at  $t$  from  $t-1$
- Have been used in many areas such as bioinformatics, robotics, etc
- Model contains both observable and unobservable states
- Hidden states combine unobservable interactions
- Flexibility of user defined observable states
- Smoothing, disregarding outliers
- Weighting, can weigh phases based on number of occurrences



## Motivation, Current Problem

Current DVFS Techniques

Phases and Hidden Markov Models

## Proposed Approach

Phased-Based DVFS, *PVFS*

Initialization

Training

Applying

## Experimental Results

Setup

Observed HMMs

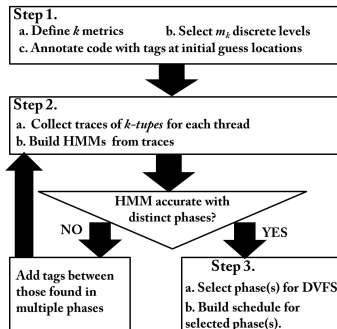
Major Results

## Steps to Apply PVFS

- Parametrization
- Training
- Applying

## Parametrization

- *System Metric*, a simple measurement of system
- *Free Parameter Set*, a collection of system metrics to describe performance and power
- Discretization, a distribution that matches the system metric and application



# Phase-Based DVFS *PVFS*

## Training

- Tag used to collect observation
- Tags placement can be automated
- Initial placement
  - Beginning/End of function
  - Beginning/End of loops
  - Beginning/End of large blocks
- Update tag placement
  - Use of Viterbi Path to decide if need additional tags
  - Hidden state found with low probability and contains multiple tags with diverse performance/power
  - When a tag id is semi-uniformly distributed between hidden states

## Evaluation of Model

- Probability the sequence of the Viterbi Path mates a sample trace
- No new tags needed

---

### Algorithm 1 Initial placement of tags in C code.

---

```

1: for all Source Files do
2:   Find beginning of function based on regex
3:   Place tag at location
4:   Scan through function for LOOP using regex
5:   Scan for end of LOOP by matching "{" and "}"
6:   if LOOP length is greater than 4 then
7:     Place tag at beginning location of LOOP
8:     Place tag at end location of LOOP
9:   end if
10:  Scan for end of function by matching "{" and "}"
11: end for

```

---



---

### Algorithm 2 Update tags in C code.

---

```

1: Let T be the set of critical tags
2: Add tags to T from hidden states with probability <  $\tau$  and
   number of tags >  $\gamma$ 
3: for all Tags (t) in the HMM do
4:   for all Hidden State (h) do
5:     if  $100/|H| - \epsilon \leq \text{Probability}(t) \in h \leq 100/|H| + \epsilon$  then
6:       Add t to T
7:     end if
8:   end for
9: end for
10: for all t in T do
11:  Scan for function call, loop, or control statement from t
12:  Add tag at found location
13: end for

```

---

## Applying

- Hidden states (Phases) with power performance and high power
- Tags can be used to signal DVFS

## Discussion

- Hardware
  - Multiple levels of controller - HMM for each control
  - Heterogeneous processors - Tag based on device and HMM for each
  - GPU - Breaking execution into warps, thread blocks, etc
- Complexity
  - Let  $T$  be the number of time steps
  - Let  $S$  be the number of hidden states
  - Traditional Baum-Welsh,  $O(TS^2)$
  - Long codes will increase the training time in a linear fashion
  - $S$  tends to be small, will be on discretization of system metrics

## Motivation, Current Problem

- Current DVFS Techniques

- Phases and Hidden Markov Models

## Proposed Approach

- Phased-Based DVFS, *PVFS*

- Initialization

- Training

- Applying

## Experimental Results

- Setup

- Observed HMMs

- Major Results

# Experimental Setup

## Simulation

- Chip simulation, Sniper
- Memory Simulation, McPAT
- NoC simulation, DSENT

*Simulated chip description.*

Core	22nm Ivybridge
L1 cache	32KB, 8-way associative, Access Latency: 4 cycles
L2 Cache	256KB, 8-way associative, Access Latency: 8 cycles
Coherence	MESI
L3 Cache	2MB/core, Shared, 16-way, Access Latency: 30 cycles
NoC	2 cycles latency; 64 bits/cycle 16 cores (4x4); 32 cores (8x4)
DVFS Latency	2 usecs (Both core and NoC)
DRAM	45 nsecs Latency; DDR3-1600; per-controller b/w: 7.6 GB/sec; 4-8 cores use 1 controller; 16-32 cores use 4 controllers

## Comparison Methods

- Energy Limit (EL)
 
$$EL(app, p) = T(app, p, baseline) \times \min(P(app, p, baseline))$$
- Energy Delay Product (EDP)
  - Time-Driven DVFS, Swaminathan et al. <sup>a</sup>
  - Change at every epoch
  - Fixed epoch size
  - Tuned tolerance parameter  $\gamma$

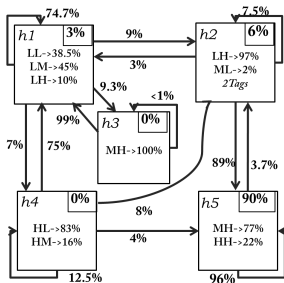
---

<sup>a</sup>Improving energy efficiency of multi-threaded applications using heterogeneous CMOS-TFET

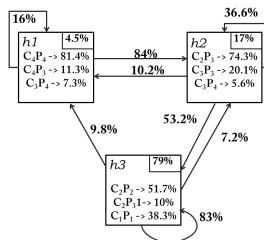
## Experimental Setup

### Benchmark Suite

- Freqmine, *Frequent itemset mining*, PARSEC
  - Tree and sorting algorithms. Common in data mining.
- Dedup, *Data deduplication compression*, PARSEC
  - Compression algorithm using pthreads.
- Mgrid, *Multigrid solver*, SPECOMP
  - V-cycle, has variable levels of parallelism through V-cycle.
- Wupwise, *Quantum chromodynamics*, SPECOMP
  - Lattice based quark propagation.
- XSBench (MC) , *Monte-Carlo transport*, CORAL
  - Monte Carlo neutronics, read/write intensive. Low performance.
- LCALS, *Collection of loops*, CORAL
  - Loops that represents float-point execution patterns from multiple applications.
- CoMD, *Molecular dynamics*, MANTEVO
  - Execution pattern varies as molecules between cells. Different patterns in and between cells.
- HPCCG, *Irregular conjugate gradients*, MANTEVO
  - Test system sparse computation. Gives a comparison bound to LINPACK



+

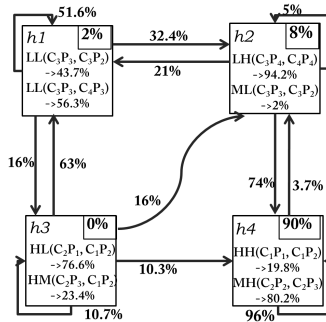


## HMM with Core

- 5 hidden states
- $h1$  and  $h2$  to reduce power
- Tags correspond to irregular data access and thread barriers
- Reduced by .8v

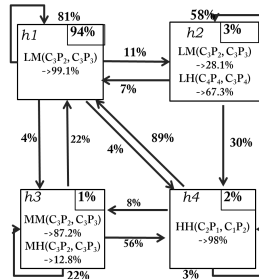
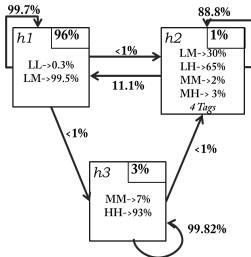
## HMM with Network

- Power due to network contention is a small fraction of the power
- Due to this model DVFS would be applied to  $h2$
- Tags do not coordinate to those in the core model



## HMM of Core and Network

- DVFS on  $h2$
- These tags are slightly different than those of both models
- Reduce to .8V
- Reduce energy by 8.78%

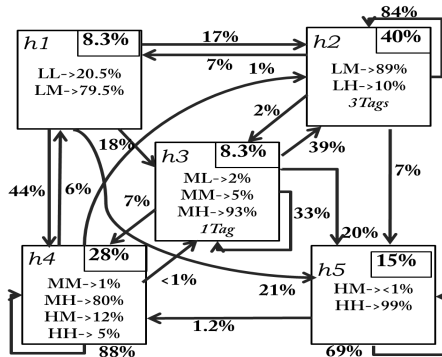


## HMM of Core

- 15 Tags to capture the 7 unique loops
- 4 Tags to apply DVFS, irregular long strided access
- A reduction of 7.1%

## HMM of Core and Network

- A network only model will only have one phase, similar network contention
- Both together, 16 Tags, 2 tags for DVFS
- A reduction of 7.9%

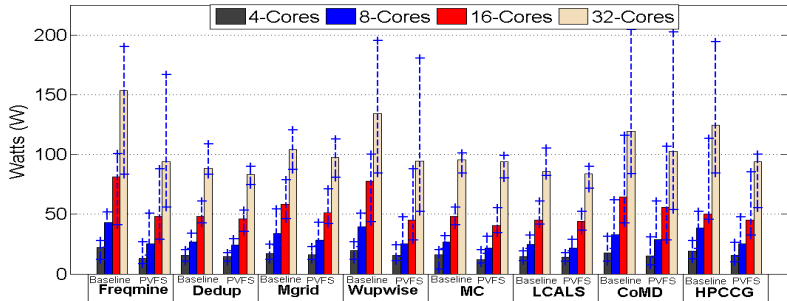


## HMM of Core and Network

- Most complicated model of test suite
- 14 tags are found and used
- 2 Phases to apply DVFS
- Reducing 9.8% energy

# Raw Effect on Dynamic Power

*Dynamic Power with and without PVFS*

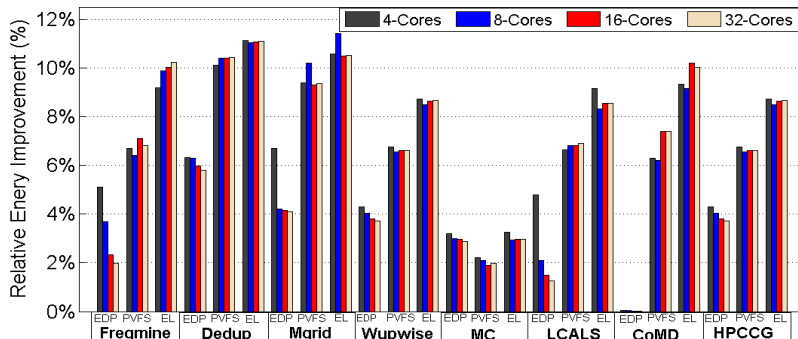


- Baseline without DVFS and PVFS dynamic power
- Reduction of maximum and average power for all applications
- Reduction of 97 Watts for maximum power and 62 Watts on average on 32 cores
- Leakage Power is fixed, energy will go up with time penalty

	4-Core	8-Core	16-Core	32-Core
Leakage Power	1.82W	3.15W	7.53W	15.27W

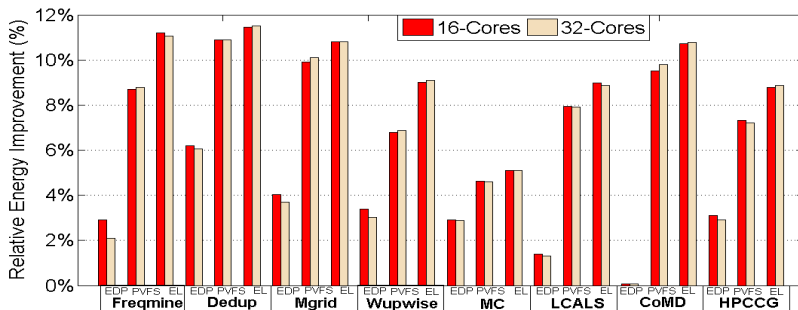
*Leakage power of simulated processors in Watts (W).*

*Relative Energy Improvement (REI)*



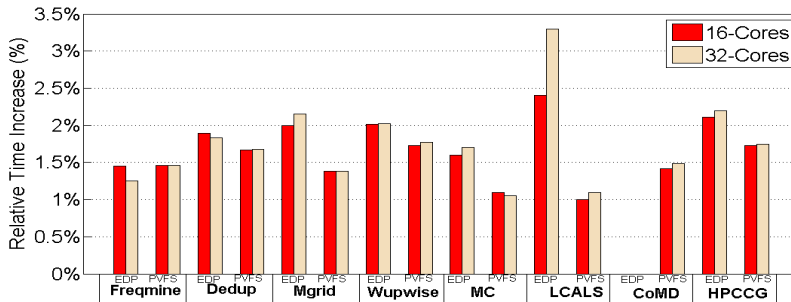
- $REI(app, p, m) = \frac{E(app, p, baseline) - E(app, p, m)}{E(app, p, baseline)}$
- With only 32 core DVFS, can achieve over 6% on 4 applications
- EL provides guide for the best possible energy use of an application
- PVFS in worst case achieves 64% of EL and 94% of EL for Dedup

*Relative Energy Improvement*



- Larger saving using DVFS on NoC, No Lose is hard.
- Worst case achieves 75% of EL
- Best case achieves 95% of EL

*Relative time increase  $RTI(app,p,m)$  chip and network*



- $RTI(app,p,m) = \frac{T(app,p,m) - T(app,p,baseline)}{T(app,p,baseline)}$
- Every DVFS method has some impact on performance
- EDP has slightly higher time increase

- Hidden Markov Models provides a generic framework for phase detection
- This framework is flexible enough to fit any future manycore system
- DVFS with Phase (PVFS) can achieve a large percent of the energy limit
- PVFS can model energy use of multiple controllers