Dynamic Runtime Optimizations for Systems of Heterogeneous Architectures

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Outline

• Introduction
• Problem Description
• Hierarchical Task Model
• Optimizations
• Simulation
• Experimental Results and Analysis
• Conclusion and Future Work
Introduction

- Embedded processors are becoming more heterogeneous and parallel, providing a rich area for optimizations
  - Leads to more efficient performance in similar power envelope
- Objective: Minimize energy consumption while meeting deadlines for dynamic tasks

Image credit: NVIDIA Tegra K1 Whitepaper
Problem Description (1)

- **Given:** heterogeneous computing architecture and dynamically arriving tasks
  - Sensors
  - User Input
  - Modes

- **Problem:** execute tasks in such a way that the energy consumed and deadlines missed are minimized
Problem Description (2)

- **Proposed Optimization**
  - Tasks and applications to be executed are submitted to runtime scheduler
  - Scheduler makes decisions in real-time and assigns tasks to compute nodes

- **Required Data**
  - Architecture models
  - Task models: execution time, deadlines, dependencies
Hierarchical Task Model (1)

• Models contain three characteristics of tasks
  – Execution time (per computational unit)
  – Energy consumed (per computational unit)
  – Dependency relationships between tasks

• Runtime characteristics, such as execution time, are deterministic
Hierarchical Task Model (2)

• Tasks may be dependent on other tasks
  – One-to-one
  – One-to-many
  – Many-to-one

• Number of dependent tasks may be deterministic or stochastic

• May represent data or control dependencies, we modeled both
Scheduling Algorithms (1)

- **Greedy**: Assign to most efficient node that becomes available
- **Greedy with DVFS**: Greedy schedule, then reduces frequency (F) and voltage (V) to lowest speed that meets deadline
- **Time-Window (TW)**: Waits for time window $W$, for most efficient resource to become available
- **Time-Window with DVFS**: Schedules as TW, but reduces $F$ to lowest speed that meets deadline
Scheduling Algorithms (2)

- **Time-Window with Local Queues (LQ):** New data structure to keep track of execution times for each task in local resource queues. Tasks submitted to local queues in each compute node.

- **Time-Window with Local Queues and DVFS:** Schedules with lowest $F$ and $V$ that still meets deadline.

- **Runtime DVFS Adjustment:** Works in conjunction with algorithms that have LQ enabled.
  - Allows a local scheduler on each resource to modify DVFS parameters for each task in its local queue.
Simulation Tool Introduction

• Created simulator to collect data on performance of scheduling algorithms
• Simulated scheduling decisions and resource availability, not task execution
• Scenario generator used to convert description of tasks, periods, and deadlines to an instantiated scenario
Simulation Tool Details

• Modularity of scheduler allows different schedules to be implemented

• Event queue tracks task arrivals, execution completion, window expiring, etc.

• Resources
  – Current task and voltage/frequency pair
  – Future tasks in queue
Experimental Setup (1)

- Representative task set scenario
  - Probabilistic number of dependent tasks, noted by labeling edges
  - Various modes
- Metrics: energy consumed, number of missed deadlines
- Baseline for comparison: Greedy
- For each algorithm, 10 runs of 10,000 periods were simulated
- Task modeling populated using experimental results and projections

<table>
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<th>P₀</th>
<th>P⁻</th>
<th>n_max</th>
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Parameters for Modes and n2
Experimental Setup (2)

- Assumption: computational units (CU) may have different Dynamic Voltage and Frequency Scaling (DVFS) levels and are turned off when not in use.
- Communication cost is paid by the producer.
- Three systems represent nodes based on scaling.
Experimental Results and Analysis (1)

- Use of local processor queues brings large improvement by leveraging known runtimes
- DVFS brings performance slightly higher
- Runtime adjustment brings no further improvement in this case

<table>
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<th></th>
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<th>14nm</th>
<th>7nm</th>
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<tr>
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<td>0.71%</td>
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</table>

Standard Deviation for 10,000 Periods

Normalized Improvement Factors (28nm Scenario)
• Improvement factors decrease due to more available resources, but same application scenario

![Normalized Improvement Factors (14nm Scenario)](image1)

![Normalized Improvement Factors (7nm Scenario)](image2)
Conclusion and Future Work

• Evaluated a number of dynamic runtime optimizations using simulation of three different heterogeneous task models
• Showed an improvement of 390x over a baseline greedy algorithm in the best case
• Greatest improvement demonstrated by Time-Window with local queues and DVFS adjustment
• Future work
  – Testing on real hardware
  – Explore other application scenarios
  – More scheduling heuristics
  – Refine communication model
  – Computational node locality
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