Dynamic Runtime Optimizations for Systems of Heterogeneous Architectures

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Outline

- Introduction
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- Hierarchical Task Model
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- Simulation
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- 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**

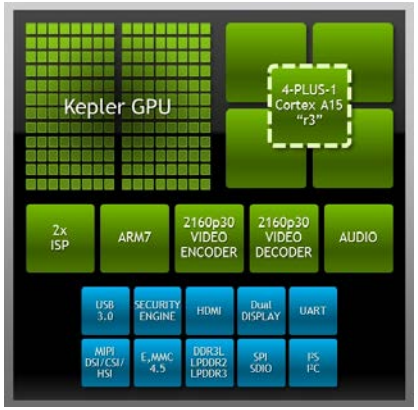


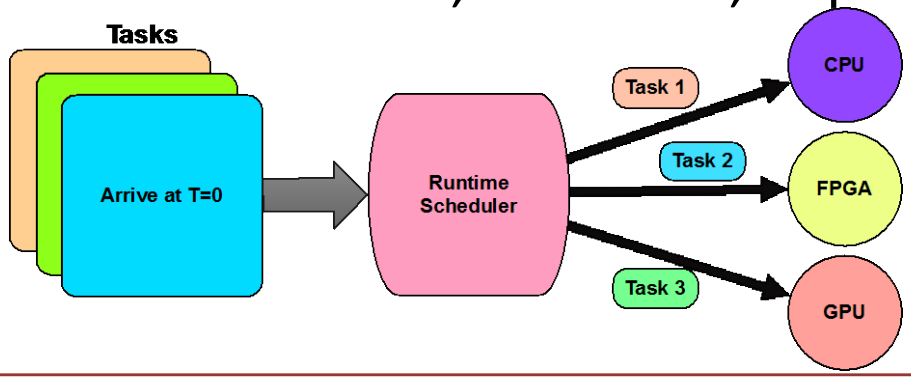
Image credit: NVIDIA Tegra K1 Whitepaper

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**

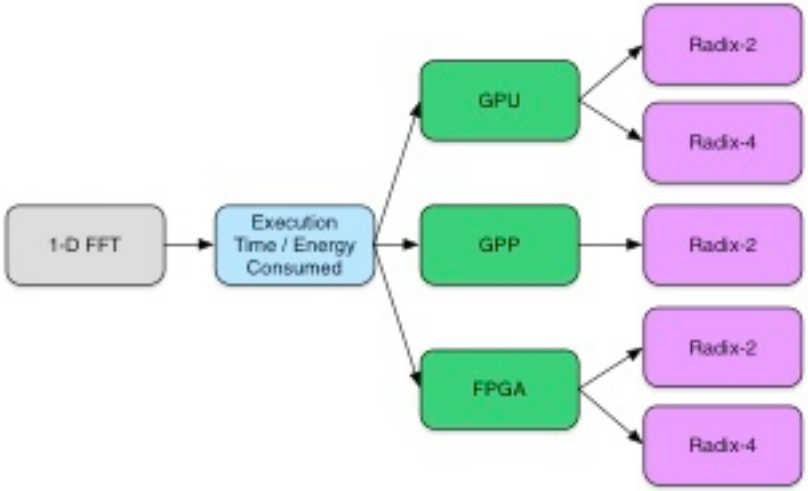
Problem Description (2)

- **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



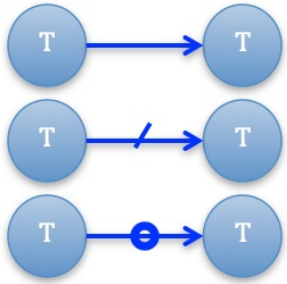
Hierarchical Task Model (1)

- **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)

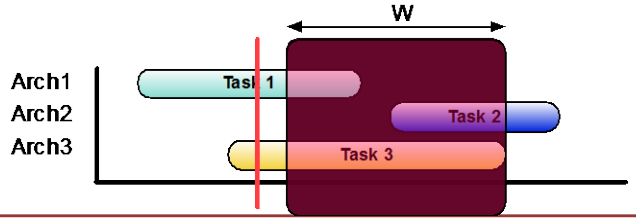
- **Tasks may be dependent on other tasks**
  - One-to-one
  - One-to-many
  - Many-to-one



- **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**

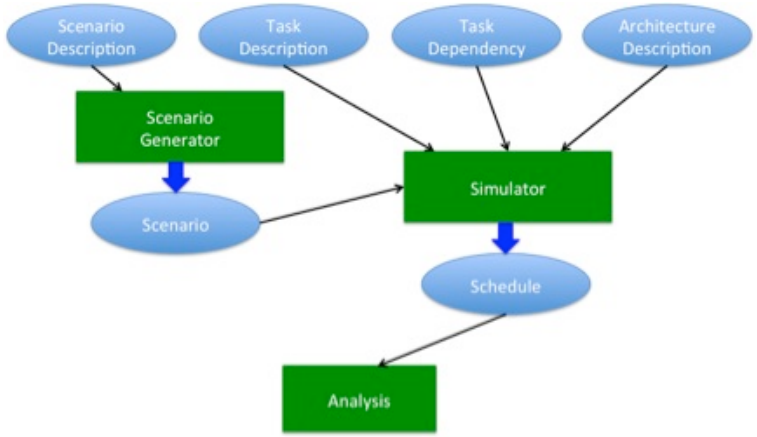


Scheduling Algorithms (2)

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

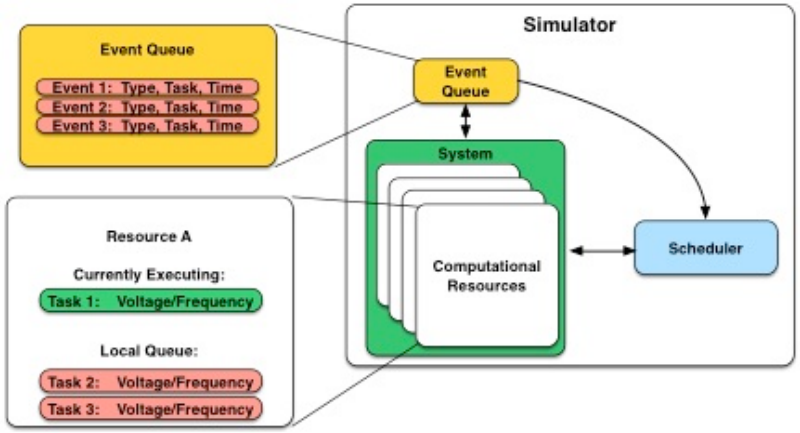
Simulation Tool Introduction

- 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



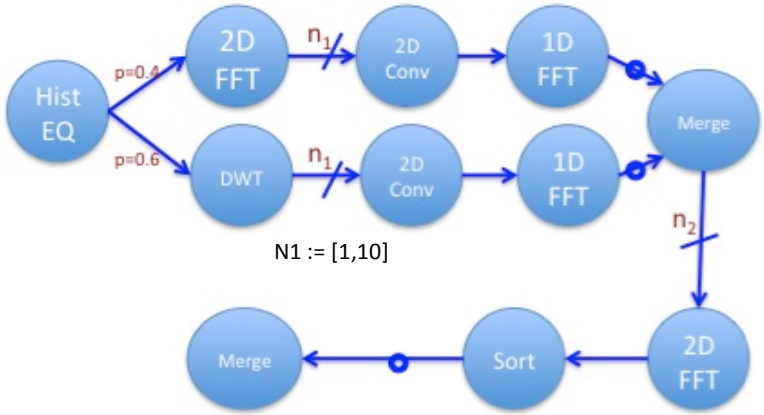
Simulation Tool Details

- **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**

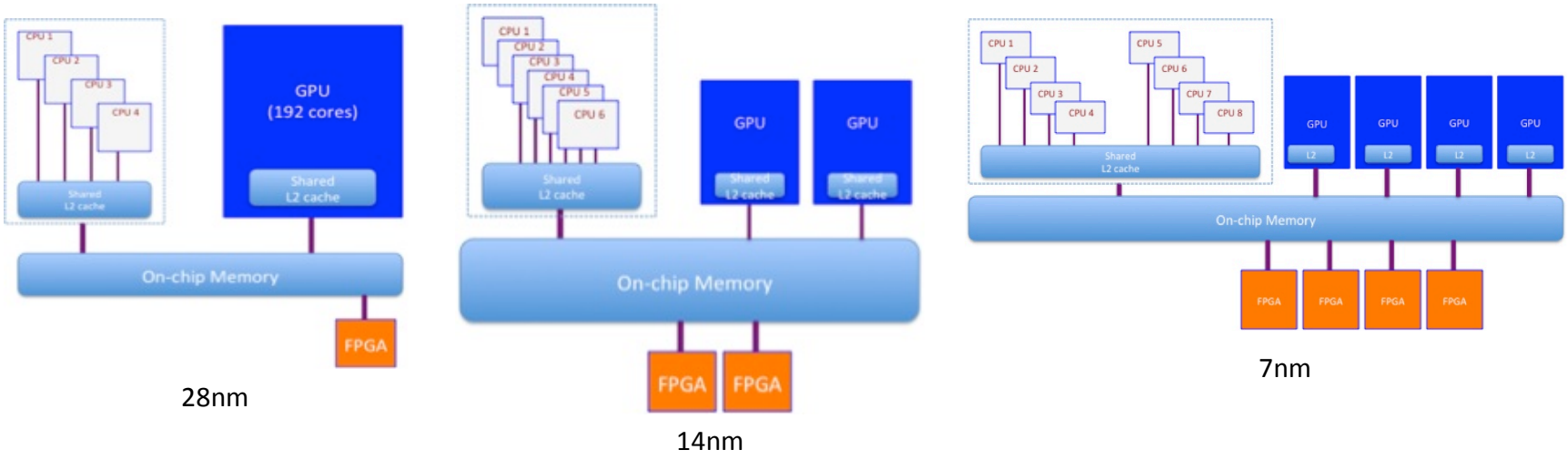


Mode	P^+	P^0	P^-	n_{max}
HI	0.5	0.3	0.2	20
MD	0.3	0.5	0.2	8
LO	0.3	0.5	0.2	2

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

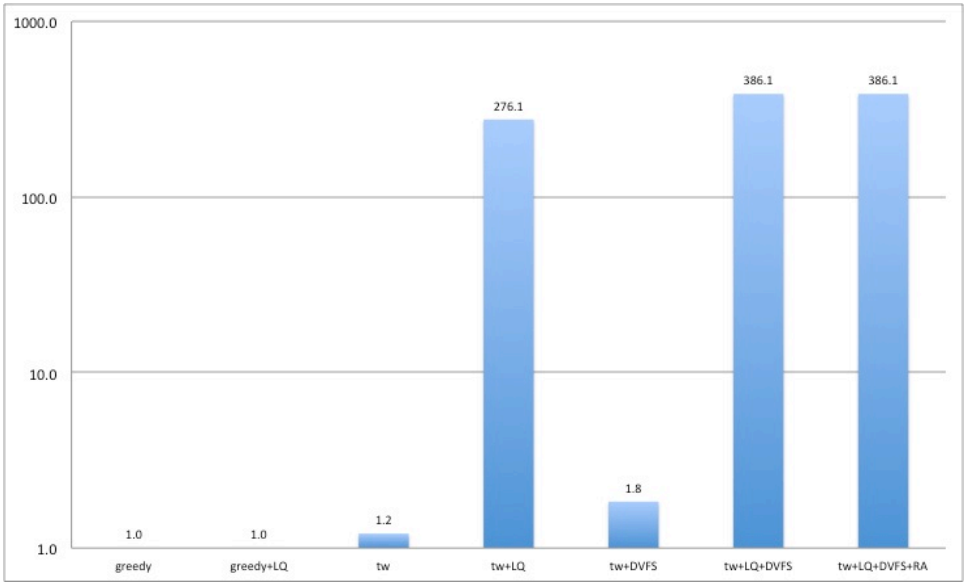


Experimental Results and Analysis (1)

- 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

	28nm	14nm	7nm
Greedy	0.00%	0.00%	0.00%
Greedy+LQ	0.00%	0.00%	0.00%
TW	0.21%	0.48%	0.32%
TW+LQ	0.40%	0.71%	1.01%
TW+DVFS	0.20%	0.45%	0.30%
TW+LQ+DVFS	0.40%	0.71%	1.00%
TW+LQ+DVFS+RA	0.40%	0.71%	1.00%

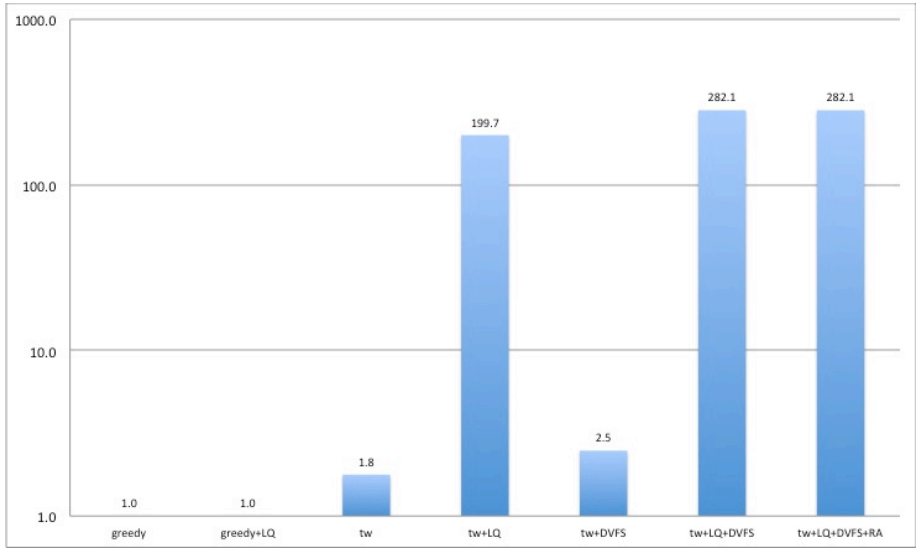
Standard Deviation for
10,000 Periods



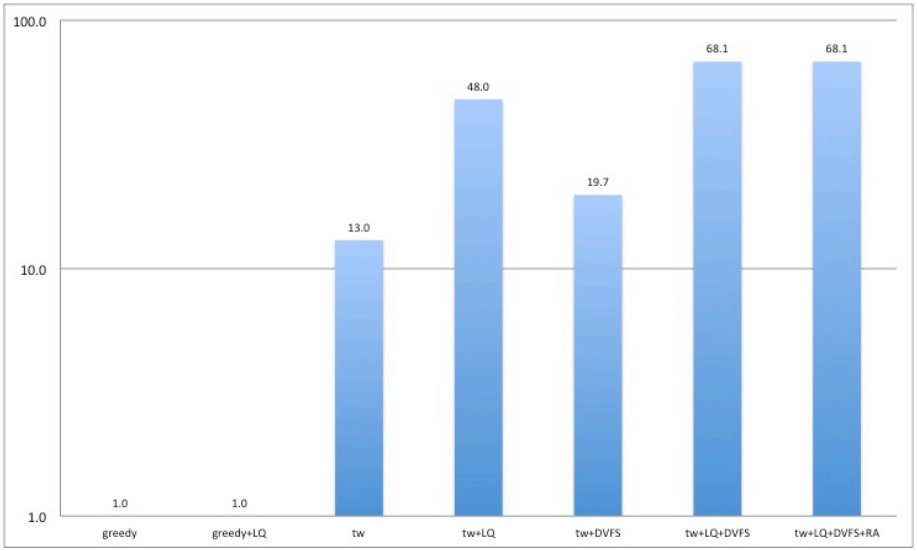
Normalized Improvement Factors (28nm Scenario)

Experimental Results and Analysis (2)

- **Improvement factors decrease due to more available resources, but same application scenario**



Normalized Improvement Factors (14nm Scenario)



Normalized Improvement Factors (7nm Scenario)

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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