Charm++ as an Energy Efficient Runtime

Power, Reliability, and Performance: One System to Rule Them All

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Interaction Between the Runtime System and the Resource Manager

- Allows dynamic interaction between the system resource manager or scheduler and the job runtime system
- Meets system-level constraints such as power caps and hardware configurations
- Achieves the objectives of both datacenter users and system administrators
Charm++ has three main components:

- **Local manager**: tracks local information such as object loads, CPU temperatures
- **Load-balancing module**: makes load-balancing decisions and redistributes load
- **Power-resiliency module**: ensures that the CPU temperatures remain below the temperature threshold, change the power cap
Support for Proactive Cooling Decisions with Neural Network-Based Temperature Prediction

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Motivation

1. Pressure of reducing the power consumption and carbon footprint of datacenters and supercomputers is increasing

2. Other expected problems include:
   - Larger process variations, temperature variations
   - More heat dissipation
   - Denser nodes with different components in the node such as GPUs, co-processors that have different temperature, cooling characteristics
Motivation

• Temperature variations among cores:
  • 7 C in idle temperatures
  • 9 C in all active temperatures
  • 20 C idle/active mixed

• Synchronous fan control:
  • 4 independent fans in the node
  • Fans all act together and cause even further temperature variation

• Reactive cooling behavior:
  • 54 W jump in fan power
  • 10 minutes stabilization time with a regular workload
Temperature Variation in Large Scale

Temperature distribution of 1800 cores

Cori at NERSC – Intel Haswell

Fit results: mean=70.53, var= 4.09

Minsky at IBM POWER8

Fit results: mean=67.88, var=3.64
Oscillatory Cooling Behavior

<table>
<thead>
<tr>
<th>CPU Utilization</th>
<th>Power Consumption of the Fans in a Node</th>
</tr>
</thead>
<tbody>
<tr>
<td>10%</td>
<td>[Graph showing power consumption]</td>
</tr>
<tr>
<td>30%</td>
<td>[Graph showing power consumption]</td>
</tr>
<tr>
<td>60%</td>
<td>[Graph showing power consumption]</td>
</tr>
<tr>
<td>99%</td>
<td>[Graph showing power consumption]</td>
</tr>
</tbody>
</table>

Workload starts 4/18/17
Fan Behavior of Different Applications
Why Temperature Modeling is Difficult?

• There are lots of parameters affecting the core temperatures:
  ◦ Complex workloads
  ◦ Ambient temperature
  ◦ Core frequencies
  ◦ Fan speed level
  ◦ Physical layout
  ◦ Hardware variations

• Combination of these parameters create an exponential modeling space
  ◦ 10 different cores
  ◦ 0-100 CPU utilization levels
  ◦ 44 different frequency levels
  ◦ 3000 RPM-10000 RPM fan speed levels
  ◦ 4 fans
  ❖ \((10^{10}) \times 44 \times (10^4) = \sim 2^{52}\)
Neural Networks for Temperature Modeling

• Neural networks are good because:
  ◦ They can capture linear and non-linear behavior between input and output parameters
  ◦ They work well in noisy data
  ◦ They do not need for formulation of an objective function

• Neural networks has been used in HPC for:
  ◦ Energy and power modeling [1]
  ◦ Performance modeling [2]
  ◦ Temperature modeling
    ◦ For GPU temperature modeling [3]
    ◦ For coarse-grained data center level modeling [4]

Neural Networks for Temperature Prediction

Experimental Setup:
- Firestone cluster at IBM with Power 8 processors
- 1 node = 2 sockets, 20 physical cores, 160 SMT cores
- OCC, and BMC for temperature, power readings
Neural Network Configuration and Validation

- We test different back-propagation algorithms with different time and memory requirements.

- Other configurations include number of layers, and number of neurons.
Model Guided Proactive Cooling Decisions

1. Fan control
   ◦ This can reduce chip-to-chip temperature variations.
   ◦ What should be the fan speed level to be able keep the chips at a certain temperature limit?

2. Load balancing
   ◦ This can remove core-to-core, as well as chip-to-chip temperature variations.
   ◦ What would the core temperatures become if a certain amount of data is moved from one core to another?

3. DVFS
   ◦ Chip-level DVFS can reduce chip-to-chip, core level DVFS core-to-core temperature variations.
   ◦ What frequency level we need to set for the cores to stay under a temperature limit for a workload?
Model Guided Proactive Cooling Decisions

1. Fan control
   ◦ This can reduce chip-to-chip temperature variations.
   ◦ What should be the fan speed level to be able keep the chips at a certain temperature limit?
Proactive Fan Control Mechanism

- The key idea is cool the processor proactively, for example, before the application starts.

- Preemptive fan-control removes temperature peaks, and is able to keep the temperature as the same level as reactive fan control.

- It can be done via job scheduler, and/or runtime without taking over the total control of the fan.
Power Reductions With Proactive Cooling

Maximum versus Stable Fan Power of Each Node

Power Reduction = Maximum Power – Stable Power

35% reduction in fan power
Decoupling the Fans

18% reduction in fan power
# Total Reduction in Fan Power

<table>
<thead>
<tr>
<th>Optimization</th>
<th>Benchmarks</th>
<th>DGEMM</th>
<th>Stencil3D</th>
<th>kNeighbor</th>
<th>LeanMD</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reactive Fan Control</td>
<td></td>
<td>5868 W</td>
<td>13433 W</td>
<td>6769 W</td>
<td>6770 W</td>
<td>8210 W</td>
</tr>
<tr>
<td>Preemptive Fan Control</td>
<td></td>
<td>3893 W</td>
<td>8526 W</td>
<td>4381 W</td>
<td>4224 W</td>
<td>5256 W</td>
</tr>
<tr>
<td>Preemptive and Decoupled Fan Control</td>
<td></td>
<td>3179 W</td>
<td>7972 W</td>
<td>3765 W</td>
<td>3569 W</td>
<td>4621 W</td>
</tr>
<tr>
<td>Total Power Reduction (%)</td>
<td></td>
<td>45.8</td>
<td>59.3</td>
<td>55.6</td>
<td>52.7</td>
<td>53.3</td>
</tr>
</tbody>
</table>

53% reduction in fan power on average
Remaining Temperature Variation

Fit results: mean=70.79, var=1.90

• DVFS?
• Load Balancing?
Temperature-Aware Load Balancing With Charm++

• Load balancing can help reduce the temperature variations, but how do we decide how much load to move?

• Charm++ [1] has an runtime database which stores:
  • Number of tasks per process
  • Load of each object (in terms of execution time)
  • Communication load of each object

• Load balancing is triggered periodically with customizable periods

• We implement our temperature-aware model guided load balancing algorithm.

• Load balancing has potential to remove both chip and core level variations.

Conclusion

• In summary, we propose:
  ◦ A neural-network based temperature prediction model
  ◦ Proactive cooling mechanisms:
    ◦ Fan control
    ◦ Load balancing

• Our results shows:
  ◦ We can accurately predict core temperatures
  ◦ Peak fan power can be reduced by 53%
  ◦ Air cooling systems can be made more efficient
Thank you!
Comparison of Reactive vs Preemptive Fan Control

- The key idea is cool the processor proactively, for example, before the application starts.

- Preemptive fan-control removes temperature peaks, and is able to keep the temperature as the same level as reactive fan control.

- It can be done via job scheduler, and/or runtime without taking over the total control of the fan.
Power Reductions in Preemptive Fan Control

- Peak fan power can be reduced by 54 Watts = 58% reduction in cooling power.
- 2790 Joules of energy is saved = Red area – black area

How early to set the cooling speed?

Power Consumption of the Fans in the Node

- Reactive Fan Control
- Preemptive Fan Control

Workload Starts