OAK RIDGE National Laboratory

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Power-Capping Metric Evaluation for Improving Energy Efficiency in HPC Applications

Energy Efficiency with Sustainable Performance: Techniques, Tools, and Best Practices (EESP) Workshop at ISC High Performance

Maria Patrou[1], Thomas Wang[2], Wael Elwasif[1], Markus Eisenbach[1], Ross Miller[1], William Godoy[1] & Oscar Hernandez[1]

[1]*Oak Ridge National Laboratory, Oak Ridge, Tennessee, USA*
[2]*Camas High School, Camas, Washington, USA*

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EESP WORKSHOP 2025

Overview

- Power-Capping
- Motivation
- Related Work
- HPC Application – LSMS
- Methodology
- Experimental Evaluation
- Conclusion

Power-Capping

- Power management technique that enables setting a maximum power limit on a device and it dynamically adjusts the power utilization to be under the defined limit
- New-generation architectures, such as NVIDIA’s GH200 superchip, regulate both CPU and GPU simultaneously
- It incorporates the automatic power-steering system and dynamically reallocates power between the CPU and the GPU based on their usage; preference on the CPU
- Limits are enforced through Dynamic Voltage and Frequency Scaling (DVFS) for CPU and GPU
- More significant impact on compute-intensive workloads than memory-bound tasks

Overview of the NVIDIA GH200 Superchip

Architecture

Key Features:

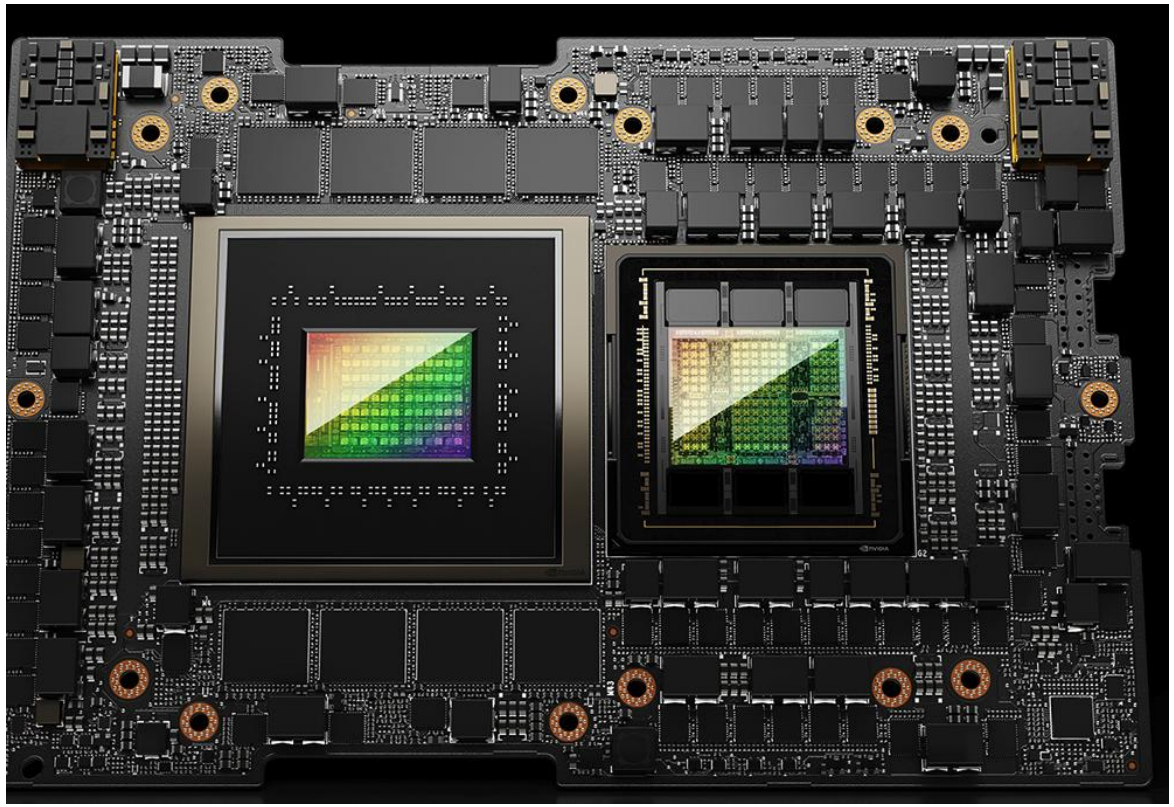
- 72-core Arm Neoverse-V2 CPU (Grace)
- Hopper GPU with 96GB HBM3
- Integrated CPU-GPU memory architecture

Peak Power Consumption: Up to 1kW

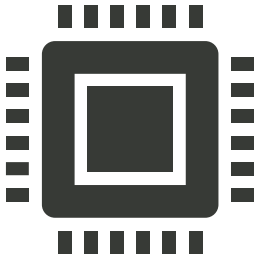
Challenges:

- Managing power across CPU, GPU, & I/O
- High-resolution monitoring for transient power spikes

NVIDIA GH200



Motivation

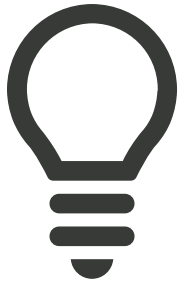


HPC Power Challenges

Increasing power consumption in modern superchips (e.g., NVIDIA GH200)

Need for fine-grained power and energy optimizations

Moore's Law slowdown and efficiency trade-offs



Why Fine-Grained Power Analysis?

Identifying power spikes and inefficiencies

Optimizing application performance and energy use

New architectures have more knobs to control power utilization.

*What **power-capping setting** is more suitable for a **GPU task** to achieve **energy efficiency**?*

Related Work

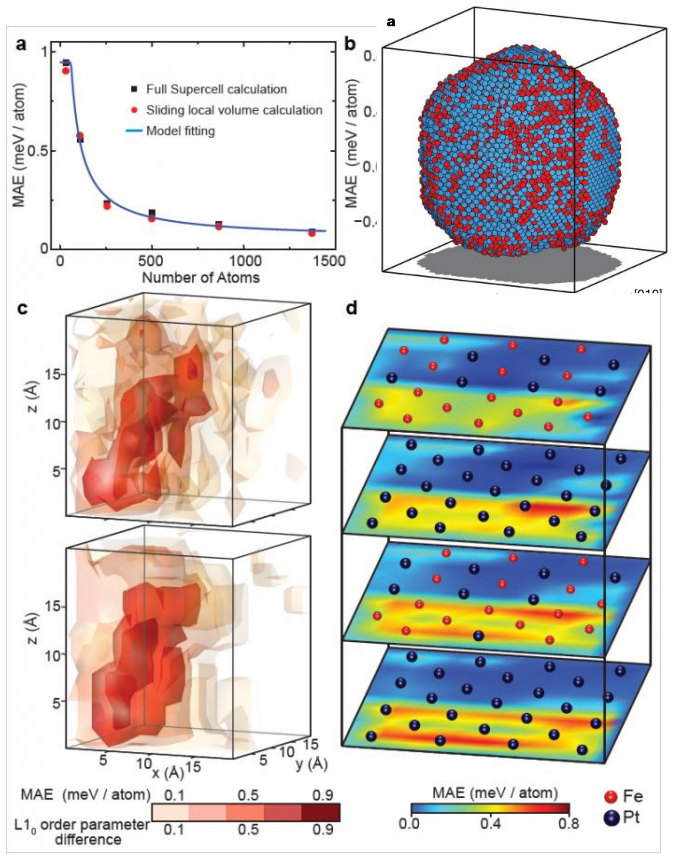
- CPU-GPU power management with heuristic or machine learning methods have been explored
- Greenup, Powerup, and Speedup (GPS-UP) framework to categorize optimizations by their impact on execution time, power, and energy efficiency
- Fine-grained power-capping strategies, such as the Global Extensible Open Power Manager have proven more effective than static limits

- We utilize the automatic power steering of the GH200 when setting a given power cap, and analyze the impact of energy and runtime performance of the most suitable power capping setting as suggested by two decision-makers metrics

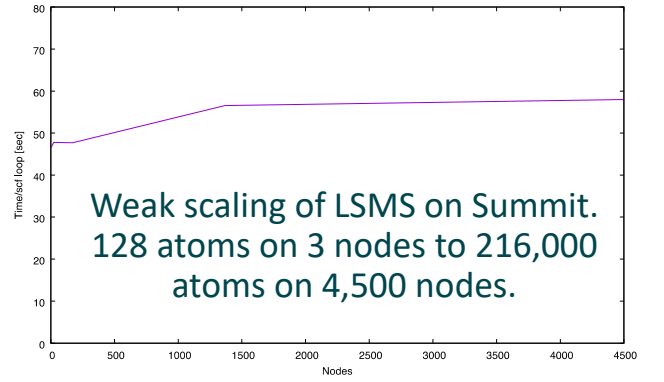
LSMS (Locally Self-consistent Multiple Scattering)
DFT First Principles Calculations for Large Systems

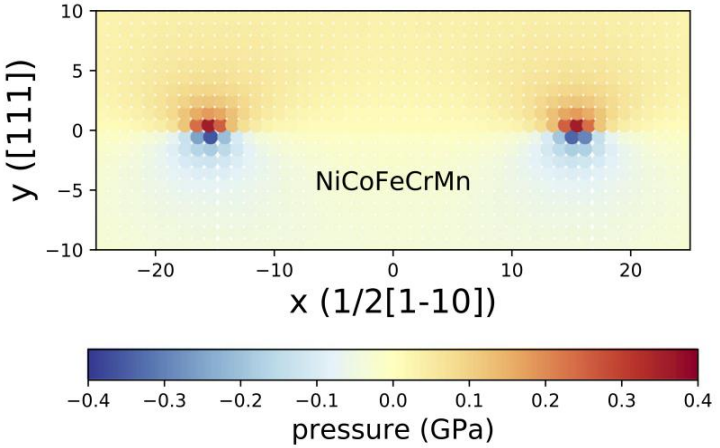
- LSMS solves the Schrödinger or Dirac equation for electrons in solids within Density Functional Theory for alloy large systems and magnetic materials.
- ORNL's exascale application
- One of the most ORNL's power-hungry HPC applications
- Open source:

https://github.com/mstsuite/lsms



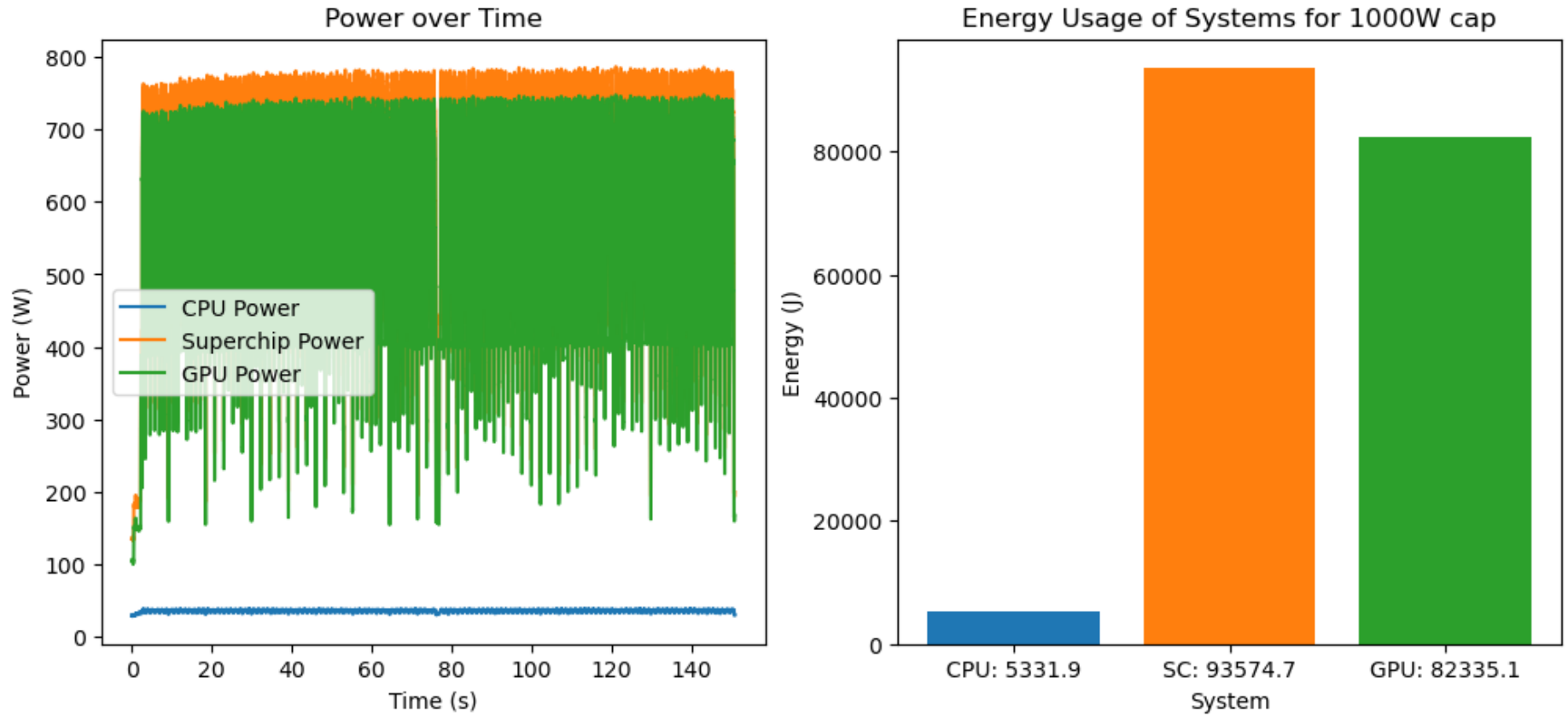
Magnetism in FePt. Nature 542, 75 (2017)





Dislocation core structure in NiCoFeCrMn alloy

HPC Application – LSMS Energy/Power Data



Power and total energy consumption, including CPU and GPU components (no power capping).

HPC Application LSMS – GPU Task Breakdown

Investigation of GPU tasks --- kernels within the application and GPU inactivity phases:

- **sm90_gemm_ts64x64x32**: Compute-intensive cuBLAS zgemm operation; typically compute-bound
- **buildKKRMatrix**: Matrix construction primarily involving memory operations; memory-bound.
- **sm90_gemm_ts32x32x32**: Another compute-intensive cuBLAS zgemm kernel; compute-bound
- **getrf_pivot** kernels: Lower-upper factorization with pivoting; constrained by random memory accesses
- **trsm_left_kernel**: Triangular matrix solve (BLAS); typically memory-bound due to data access patterns
- **gpu compute idle**: Periods in which computations only occur on the CPU

HPC Application LSMS – GPU Task Breakdown

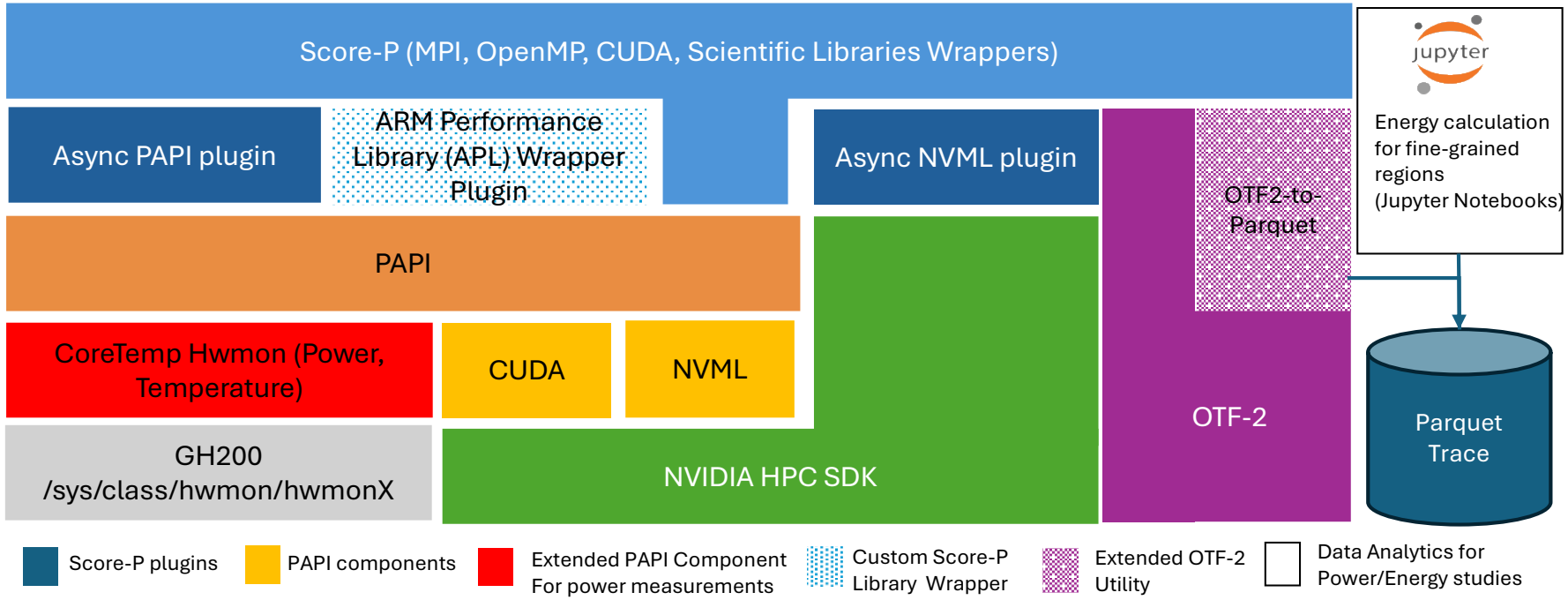
Task	Total Time (s)	# Calls	Total Energy (J)	Avg. Power (W)
sm90_gemm_ts64x64x32	77.89	21,632	35,361.83	454.02
buildKKRMatrix	34.90	128	12,867.73	368.74
sm90_gemm_ts32x32x32	8.03	94,208	4,076.98	507.51
getrf_pivot(1)	4.07	16,384	2,694.54	662.05
getrf_pivot(2)	4.07	30,720	2,670.36	656.11
trsm_left_kernel	3.57	150,272	2,328.26	651.57
getrf_pivot(3)	1.82	8,192	1,146.70	630.06
gpu compute idle	8.83	601,345	2,425.49	274.80

Measurements at the default power setting (1,000 W, no power capping) per GPU kernel and GPU compute idle time.

Methodology

- Measure energy, power and runtime performance at the superchip level for the entire application, and focus on the CPU- and GPU-level per GPU task (kernel and GPU inactivity phase)
- Incremental chip-level power constraints on NVIDIA's GH200 superchip (with automatic power-steering system), ranging from 200 W to the maximum power limit of 1,000 W (default)
- Power data collection with Score-P and custom Performance Application Programming Interface (PAPI) component designed to read power information via the Linux */sys/class/hwmon* interface
- Metrics calculation to decide on the "best" power capping settings per GPU task

The Open-Source Performance Toolkit for Power/Energy



Python Data Analytics

Extended Components

- PAPI extension for hwmon to measure Superchip and Grace CPU power
- Score-P NVML and PAPI plugins readings
- Runtime overhead per run for the power measurements was 1.3%
- OTF2-to-Parquet conversion utility
- Jupyter-based analytics for energy profiling

Supported Architectures

- GH200, potential for AMD Instinct and other platforms

Based on tools from:

VAMPIR

Score-P
Scalable performance measurement infrastructure for parallel codes

icl-utk-edu/papi

NVIDIA

arm

https://dl.acm.org/doi/10.1145/3703001.3724383

Decision-maker Metrics for "best" power capping settings

Speedup-Energy-Delay

- Calculation of speedup energy-delay from the baseline (runtime1 and energy1) - no power capping (1,000W)

$$SPEEDUP_{energy-delay} = \frac{\left[\frac{runtime_1}{runtime_n}\right]}{\left[\frac{energy_n}{energy_1}\right]} = \frac{[runtime_1 * energy_1]}{[runtime_n * energy_n]}$$

Euclidean Distance of normalized energy/runtime

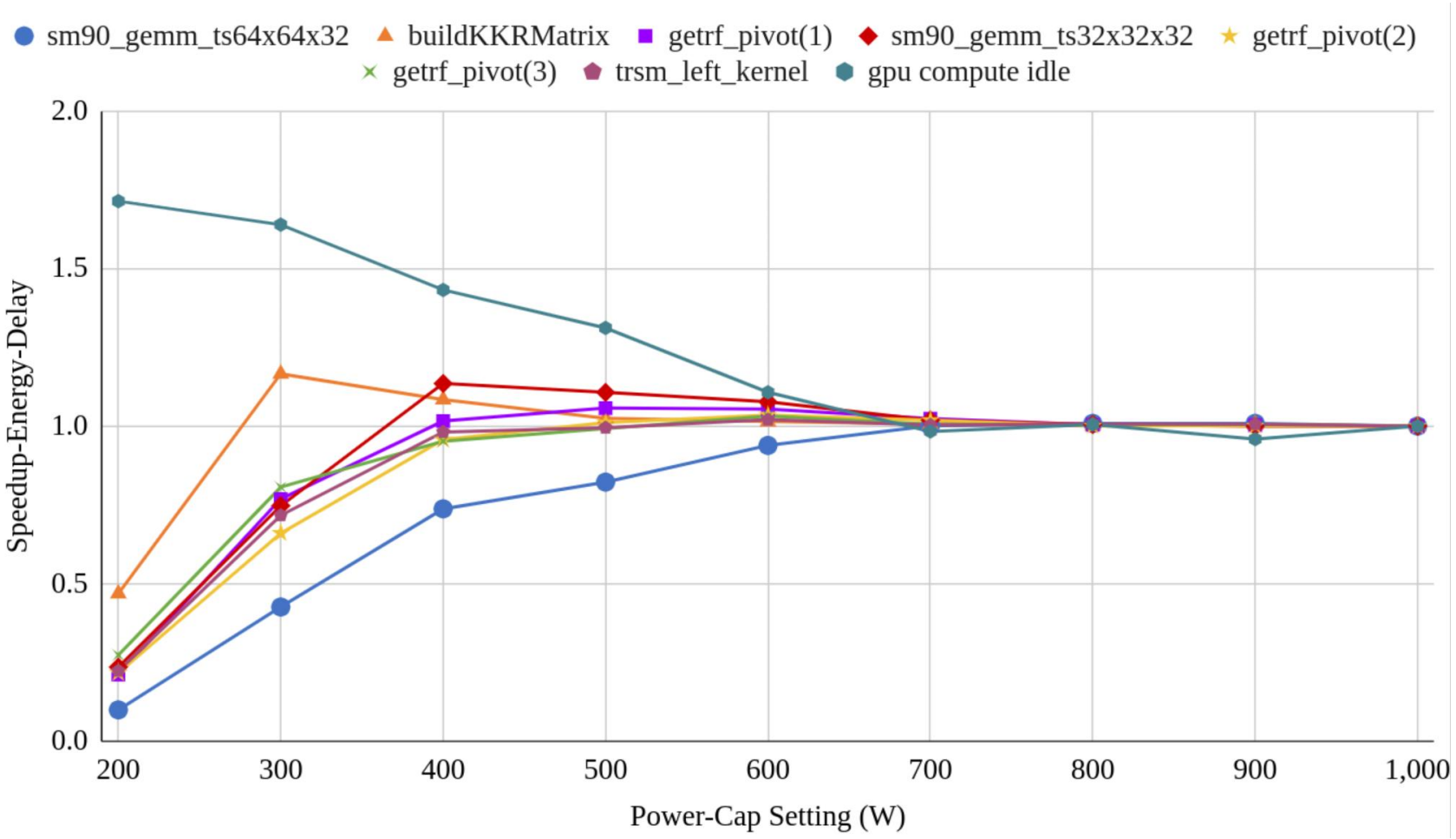
- Normalization of energy and runtime metrics using the feature scaling normalization method

$$n_{energy_{ki}} = \frac{[e_{ki} - emin_k]}{[emax_k - emin_k]}$$

- Euclidean distance of normalized energy and runtimes from point (0,0)

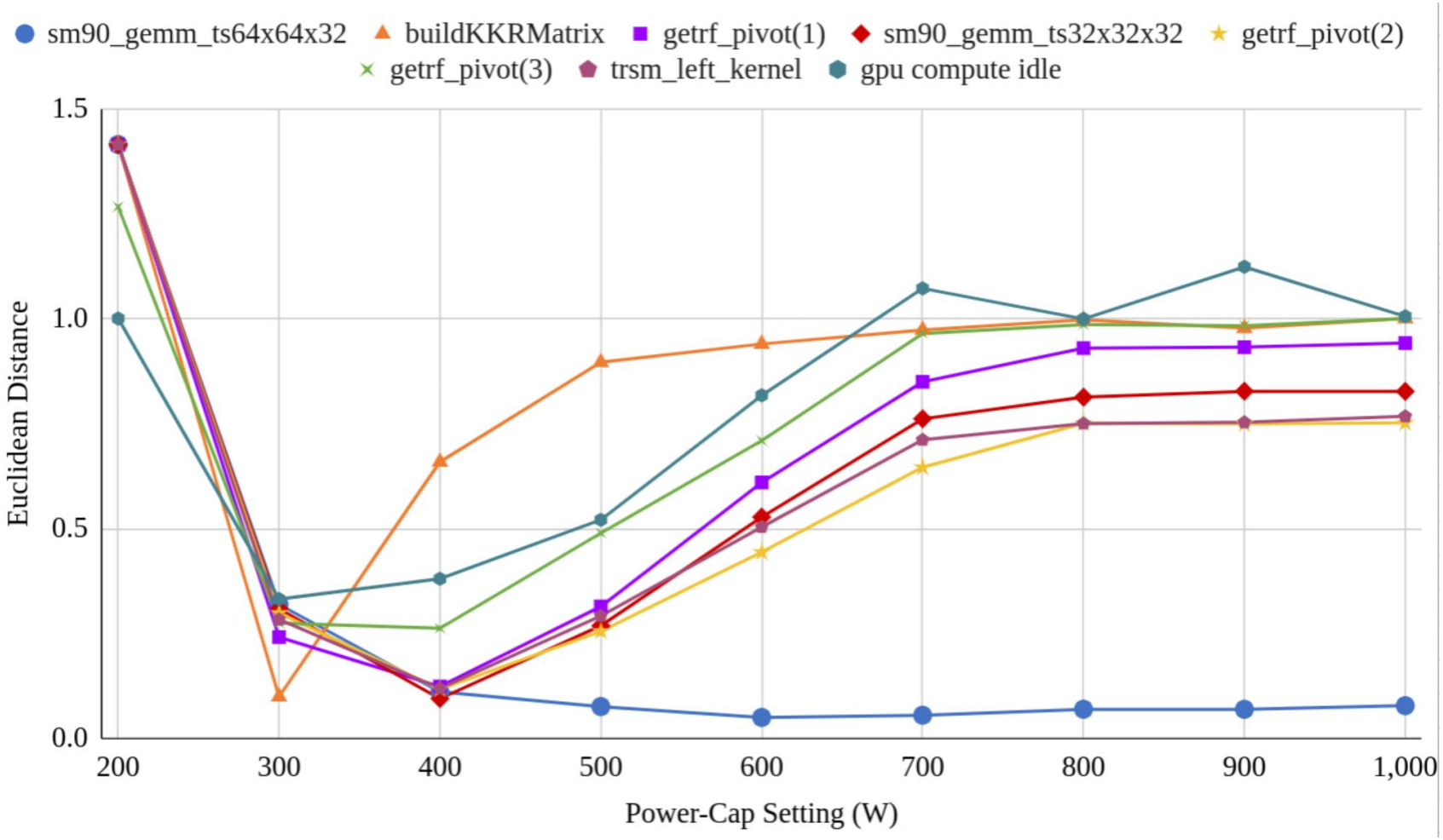
$$distance_{ki} = \sqrt{n^2_{energy_{ki}} + n^2_{runtime_{ki}}}.$$

Experimental Evaluation



Speedup-energy-delay per GPU task and power-cap setting. Higher is better.

Experimental Evaluation



Euclidean distance of normalized energy/runtime per GPU task and power-cap setting. Lower is better.

Experimental Evaluation

* SED = speedup-energy-delay
  ED = Euclidean distance

GPU task	Power Cap (W)		Energy (%)		Runtime (%)	
	SED	ED	SED	ED	SED	ED
sm90_gemm_ts64x64x32	900	600	0.85	3.42	0.00	10.3
buildKKRMatrix	300	300	22.92	22.92	11.30	11.30
sm90_gemm_ts32x32x32	400	400	31.40	31.40	28.42	28.42
getrf_pivot(1)	500	400	20.61	28.50	19.16	37.67
getrf_pivot(2)	600	400	10.05	24.48	7.37	38.41
trsm_left_kernel	600	400	9.02	25.53	7.74	36.85
getrf_pivot(3)	600	400	9.10	24.15	6.59	38.46
gpu compute idle	200	300	46.58	39.69	9.25	1.17

Runtime increase (%) and Energy reduction (%): default power compared with the most suitable power setting identified by speedup-energy-delay (SED) and Euclidean distance (ED) per GPU task.

Conclusion

- Investigation of GPU task-specific power-capping with NVIDIA GH200 superchip's automatic power-steering system
- Evaluation of two metrics—*speedup-energy-delay* and *Euclidean distance–based normalization*—to determine optimal power limits per computational GPU task
- Comparing the optimal power-capping settings suggested by each one, the Euclidean distance–based normalization is affected by the data distribution differently than the speedup-energy-delay; ED more biased towards energy
- Significant energy savings are achievable through fine-grained power management

- In the future, we will extend these methodologies, develop strategies for additional domains, and adaptive power-capping optimizations

Acknowledgments

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Thank you!

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