Power-Aware Performance: Modeling for the Physical Limits of Extreme Computing*

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together we advance_

* Presented at the Workshop on Modeling & Simulation of Systems and Applications, August 2025.

“Power is the currency of performance!”

Samuel Naffziger

SVP and Corporate Fellow, AMD

A New Era in Computing

- **The Rise of AI:**
  - Explosive growth of Large Language Models (LLMs), deep learning, and complex AI workloads
  - Demand for unprecedented computational power

- **Extreme-Scale Computing:**
  - Massive data centers, supercomputers, and specialized AI accelerators
  - Pushing hardware to its limits

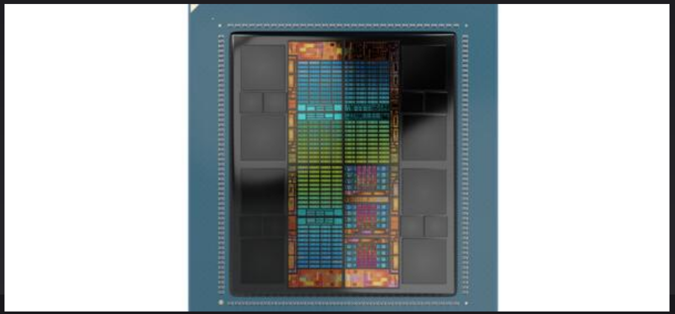
As we push the boundaries of extreme-scale computing in the AI era, power and energy have become first-order constraints

at every level of the solution stack!

Power Bottlenecks at Every Level

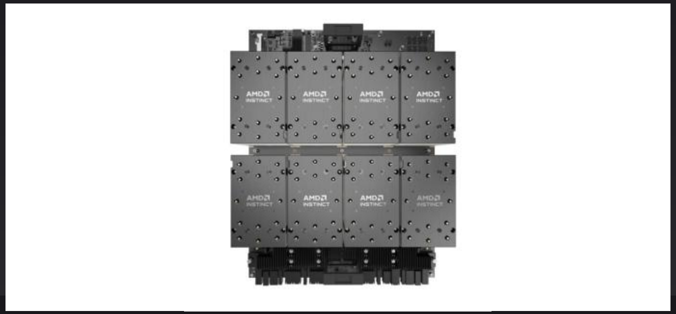
It's not just about energy efficiency

Socket



- **Physical Limits:**
  - Thermal design power (TDP) limits
  - Power delivery infrastructure constraints
  - Temperature constraints

Node



- **Platform Limits:**
  - Cooling solutions
  - Power delivery and reliability
- **Quality of Service**
  - Power = shared resource

Data Center

- **Infrastructure Impact:**
  - Data Center level voltage swings
- **Operational & Procurement Costs → TCO**
- **Environmental Impact:**
  - Growing carbon footprint

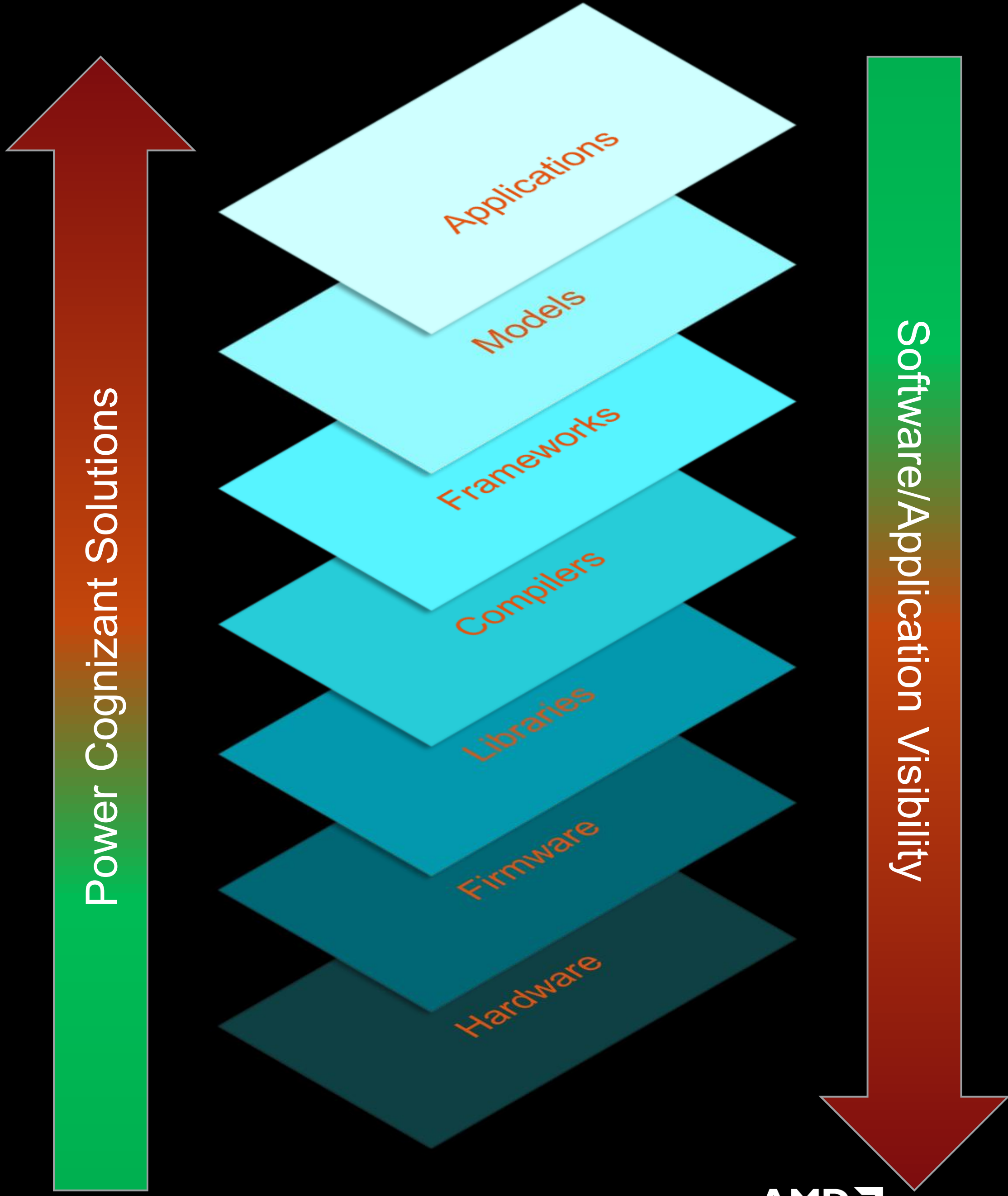
$$perf = f(power)$$

How do we model f ?

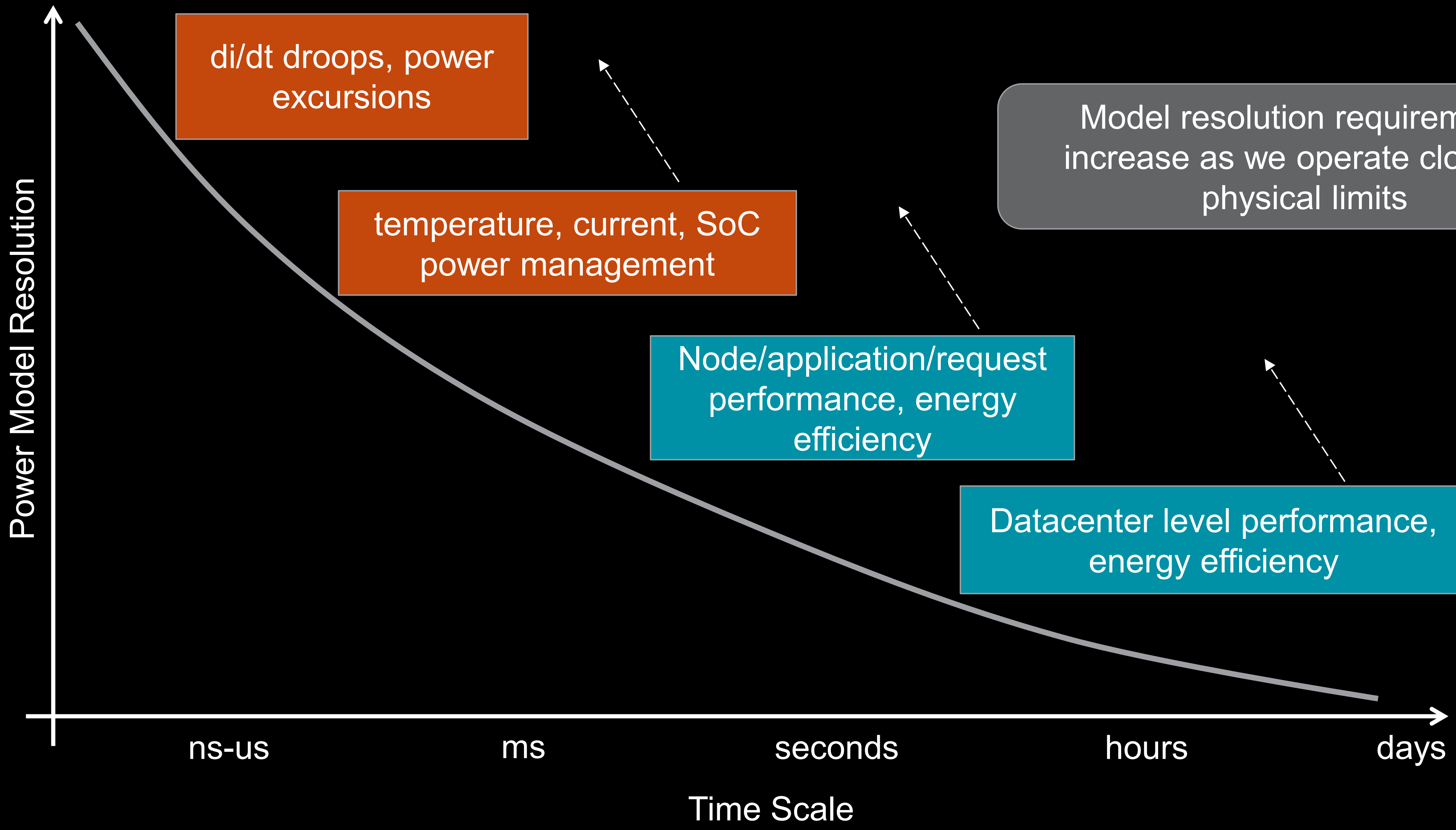
We Want Cross-Stack Transparency

- Power is not incorporated into decisions at the higher levels of software stack
- Lower levels oblivious of the software stack
- **It is critical to integrate all the "power concepts" into the SW stack**
- **And make SW more "visible" at the hardware levels**

Goal:
Power models with higher returns on performance



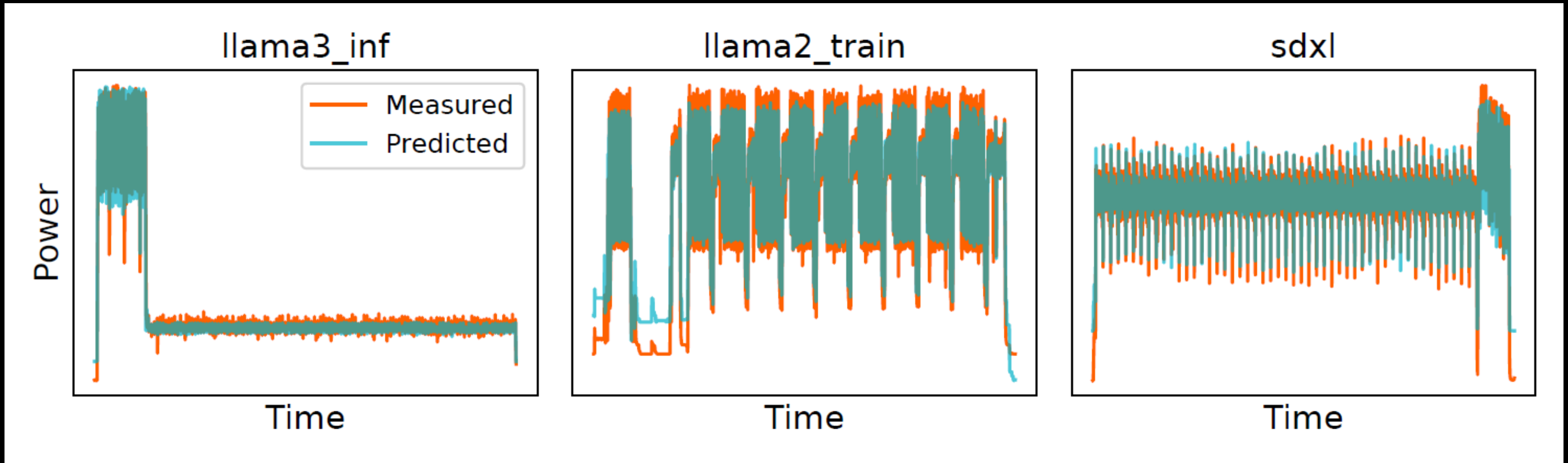
How Much Detail Do We Need?


Power Model Resolution
di/dt droops, power excursions
temperature, current, SoC power management
Node/application/request performance, energy efficiency
Datacenter level performance, energy efficiency
ns-us
ms
seconds
hours
days
Time Scale

Model resolution requirements increase as we operate closer to physical limits

Power Modeling (Estimation)

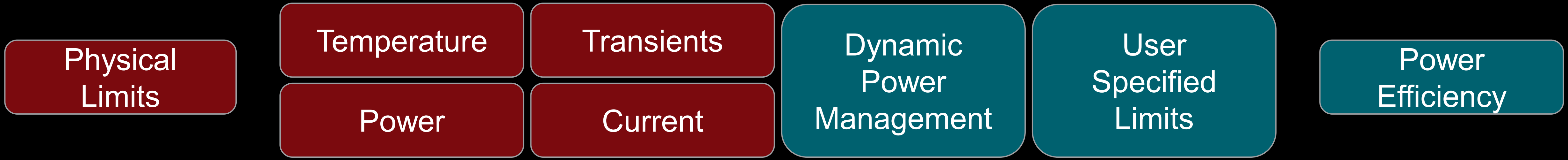
- **Power meter** => Correlate hardware events to power/energy values to build a digital power meter
  - Can be done at fine-grain resolution
  - E.g. Running Average Power Limit (RAPL)



- **Modelling performance as a function of power is complex (no simple correlation)**

What You Ask for IS NOT Always What You Get

- Performance models, compilers, SW optimizations, etc. assume a fixed frequency => **NOT THE CASE**
- Power management firmware (PMFW) and hardware limit operating frequency



Physical Limits

Temperature

Transients

Power

Current

Dynamic Power Management

User Specified Limits

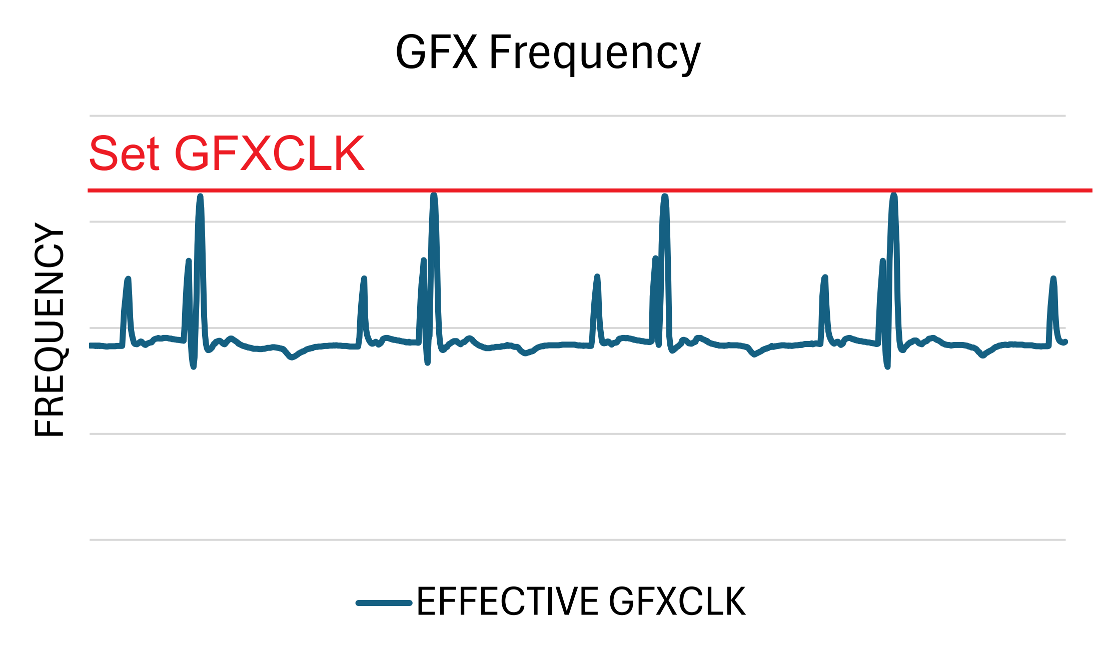
Power Efficiency

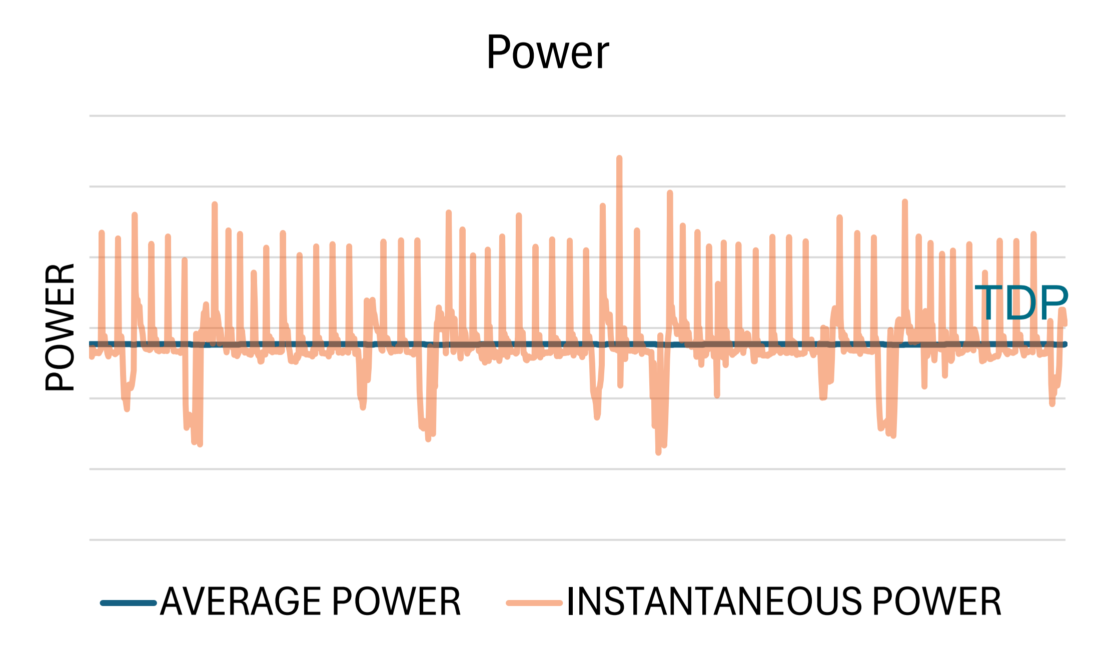
- Hardware clock modulation, firmware managed DVFS
- PMFW implements a set of algorithms and rules to manage/slosh power efficiently

Traditional Computing	Extreme Computing
$f_{effective} \approx f_{target}$	$\boldsymbol{f_{effective} < f_{target}}$

- Leads to performance non-determinism and variability and complicates modeling

Averages Hide the Details

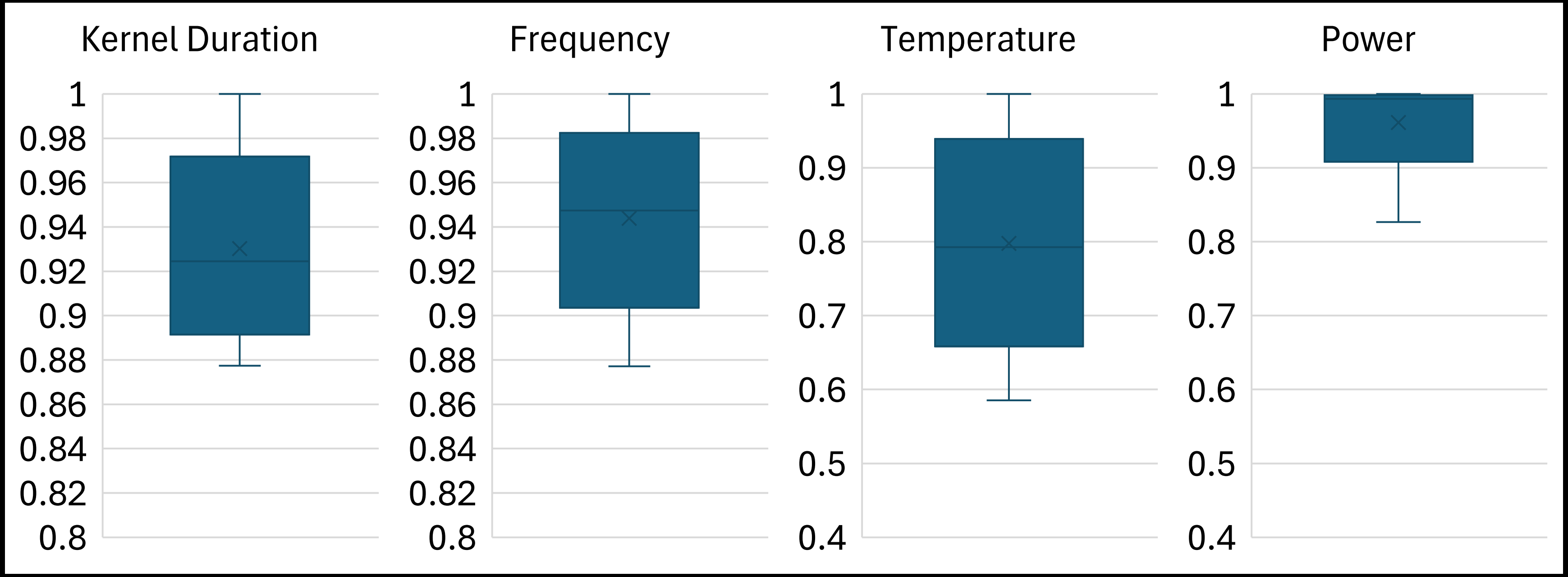




- AMD Instinct™ MI250 Accelerator running rocHPL with a set frequency of 1700MHz
- “Instantaneous Power” = high resolution average power (1ms)
- Zoomed in to 1s of total execution time
- High frequency power transients result in frequency modulation
  - Not visible when observing average power

At-scale Details Matter

- High temperature
  => higher leakage and less power available for performance
  => thermal throttling
- Slowest node impacts overall performance in synchronized run [1]



- Results for SGEMM on Longhorn cluster [1]

- LLAMA 3 diurnal 1-2% throughput variation based on time-of-day because of higher mid-day temperatures [2]

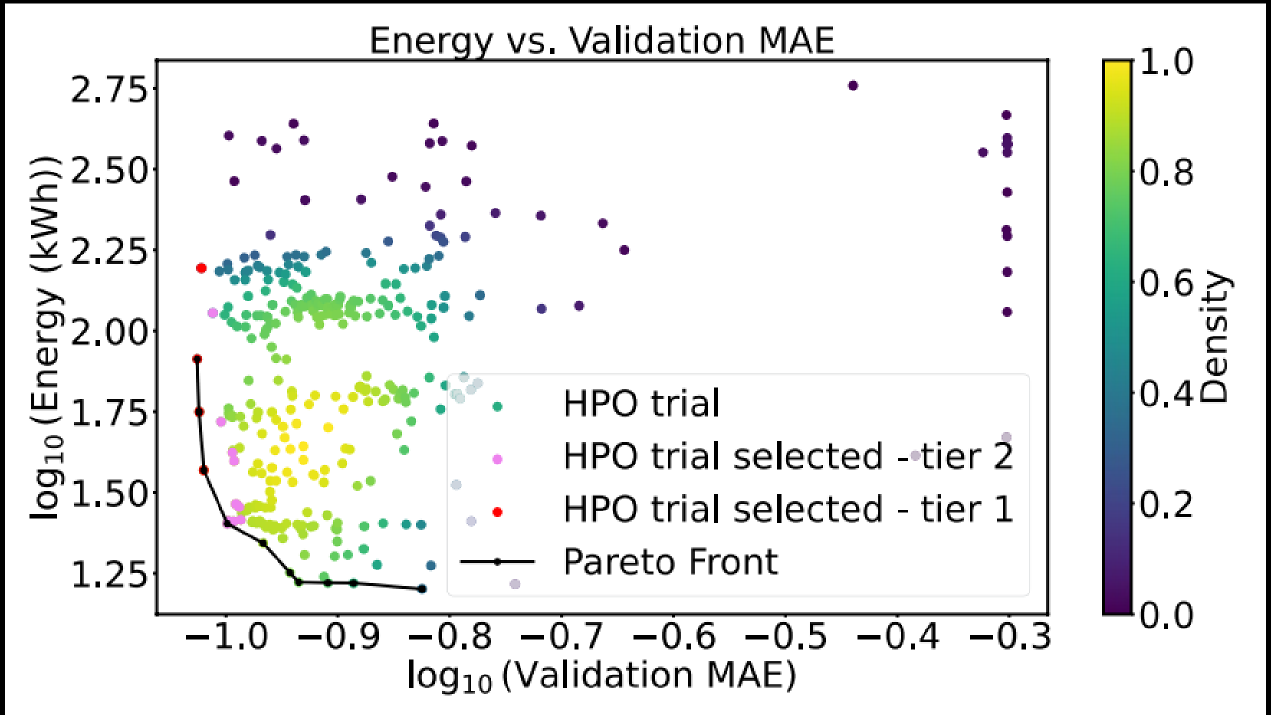
[1] Sinha, Prasoon, et al. "Not all GPUs are created equal: characterizing variability in large-scale, accelerator-rich systems." *SC22.* IEEE, 2022.
[2] Dubey, Abhimanyu, et al. "The llama 3 herd of models." *arXiv e-prints* (2024): arXiv-2407.

Omnistat – Details at Scale

Omnistat is a set of Python utilities and data collectors to support scale-out cluster telemetry targeting AMD Instinct™ GPUs/APUs

- Tracks metrics available via AMD SMI interface(s)
  - GPU and HBM utilization
  - GPU power, clock frequencies, thermals , power-caps
  - RAS error counts, throttling events, HW counters
- Low overhead (target 1% or less)
- Resource manager job tracking (SLURM, Flux, PBSPro)

Open-source: https://github.com/ROCm/omnistat

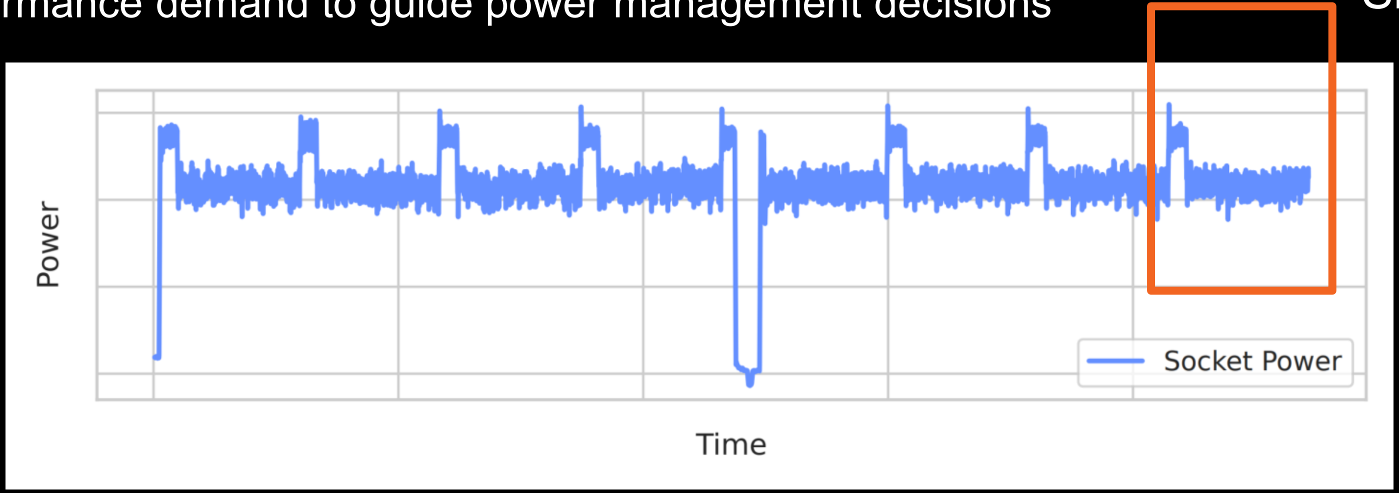


Energy efficiency hyperparameter optimization of graph foundational models trained on Frontier [3]

[3] Lupo Pasini, Massimiliano, et al. "Scalable training of trustworthy and energy-efficient predictive graph foundation models for atomistic materials modeling: a case study with HydraGNN." *The Journal of Supercomputing* 81.4 (2025): 618.

Reaction Vs. Prediction

- Current models are reactive
  - Models base their behavior on past actions
- We want predictive models, perhaps using AI or hints
  - Predict future performance demand to guide power management decisions



Llama 3.1 8B [2] – 4K/output input [reference]

- Examples
  - Predict which VMs will be active when, based on learning over large amounts of past behavior
  - LLMs repeat the same layer N times (32 for 8B, 126 for 405B)
  - Predict number of output tokens

Modeling $perf = f(power)$ is Difficult … but Necessary

Takeaways

Frequency is not constant! (What You Ask for IS NOT Always What You Get!)

Performance non-determinism and variability complicate modeling

Predictive models are more attractive

Averages hide the details and at scale details matter

Expose fine-grain telemetry to the SW stack

Create interfaces between HW and SW for power

References

- [1] Sinha, Prasoon, et al. "Not all GPUs are created equal: characterizing variability in large-scale, accelerator-rich systems." *SC22: International Conference for High Performance Computing, Networking, Storage and Analysis*. IEEE, 2022.

- [2] Dubey, Abhimanyu, et al. "The llama 3 herd of models." *arXiv e-prints* (2024): arXiv-2407.

- [3] Lupo Pasini, Massimiliano, et al. "Scalable training of trustworthy and energy-efficient predictive graph foundation models for atomistic materials modeling: a case study with HydraGNN." *The Journal of Supercomputing* 81.4 (2025): 618.

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