Simulation of the Energy Consumption of GPU

Dorra Boughzala

@Greendays - Anglet

24 June 2019

Supervisors

Laurent LEFEVRE ~ Avalon/INRIA

Anne-Cécile ORGERIE ~ Myriads/CNRS

UNIVERSITÉ DE LYON

ENS DE LYON

inventeurs du monde numérique

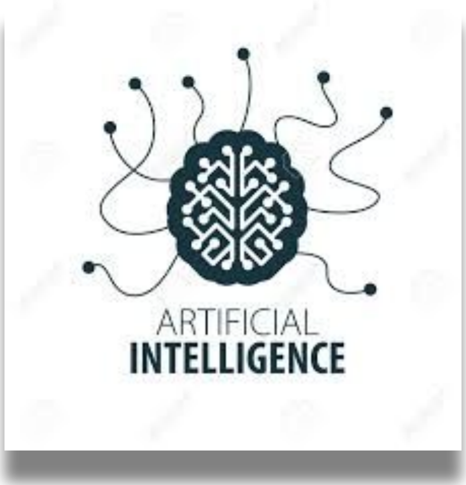
Outline

1. **Introduction**
2. **Context: GPU architecture & CUDA execution model**
3. **Our macroscopic analysis of GPU power consumption**
    a. State-of-art on GPU Power Analysis
    b. Our Methodology
    c. Experimental results & Analysis
4. **Simulating the power consumption of High Performance GPU-based Applications with SimGrid**
    a. State-of-art on GPU Power Modeling
    b. Our proposition: From SimGrid to “GPUSimGreen”
5. **Conclusion & Future works**

Why we need Exascale computing ?

Exascale computing refers to computing with systems that deliver performance with the range of 10^{18} floating points operations per second (Flops).

Source: Huffingtonpost.com



Where are we from the Exascale ?

ARCHITECTURE

- HPL performance : **148,6 PetaFlops**
- **Power consumption: 10,096 kw**
- **Power efficiency: 14,7 GFlops/watt**
- **4,608 nodes : 2 IBM POWER9 CPUs & 6 NVIDIA volta GPUs**

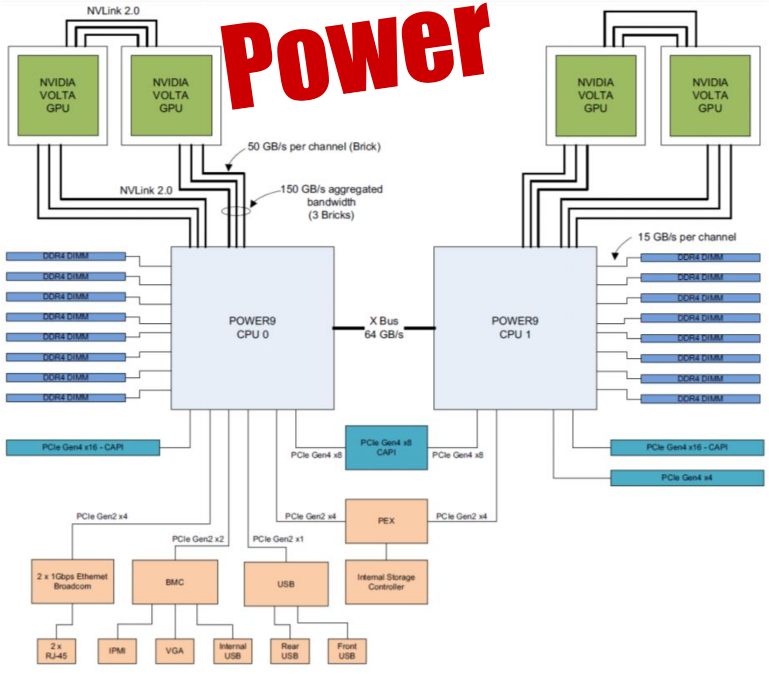
- Aurora : coming soon in **2021**
- Promise of > 1 ExaFlops
- USA or CHINA ??

“Challenges”

- Parallelism increases orders of magnitude, power consumption as well.
- The “desired” objective of consuming power to reach exascale should not exceed **20 MW**, equal to **only** 3-fold increase in energy efficiency of today most-energy efficient system in the **[Green500]**.
- **Therefore, energy has now become the leading concern for HPC system designs .**
- It’s mandatory to understand and predict power and performance profiles of current and future HPC systems and applications in order to improve their **Performance/Watt.**
- Nodes are becoming highly **heterogeneous** and **hierarchical**, modeling the power and energy consumption of such systems is a challenging task.

GPU-based computing

- GPUs have become an integral part of today mainstream computing systems thanks to their high computational power and energy efficiency.
- The CPU-GPU heterogeneous computing is more **energy-efficient** than traditional many-core parallel computing.
- Nvidia GPUs are present in five of the top 10 of **[Top500]** .



Source: Sierra **[Top500]** node architecture

My research questions are:

- How to measure and analyse the power consumption of GPUs ?
- How to predict the performance and power consumption of GPUs ? using simulation ?
- How to improve the energy efficiency of GPUs ?

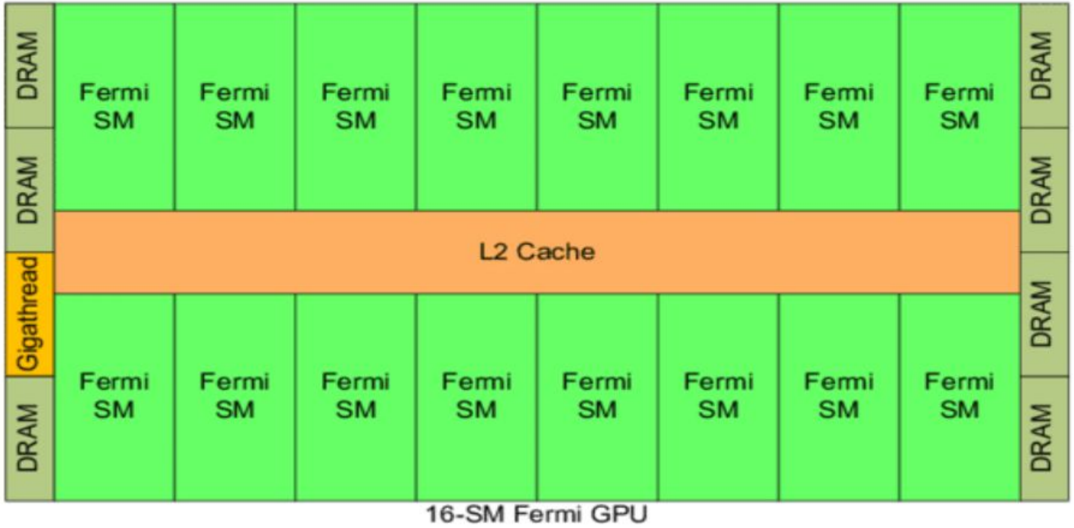
My approach is to:

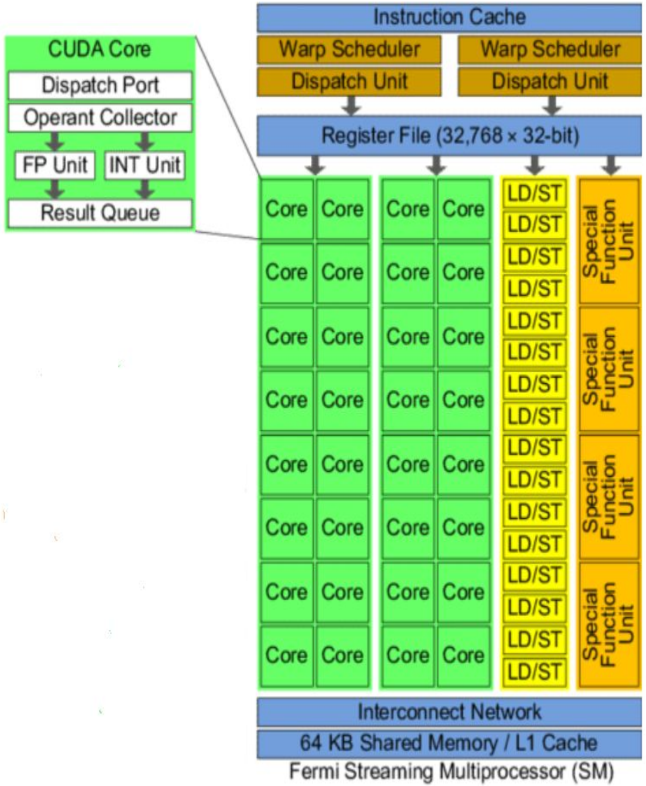
"Simulate the Energy Consumption of GPU-based systems"

1. **Power and performance profiling with real measurements**
2. **Power modeling:**
   - **Implementation in a simulator**
   - **Validation with real workloads measurements**
3. **Integration of GPU DVFS in the model for example**

NVIDIA GPU architecture

Example Fermi:





Source : NVIDIA Fermi whitepaper

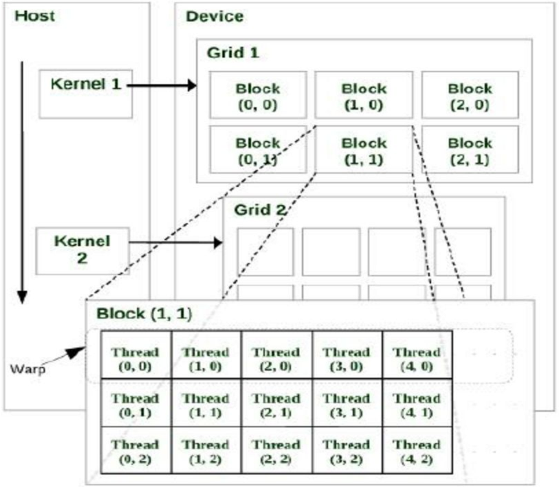
CUDA Execution Model (1)

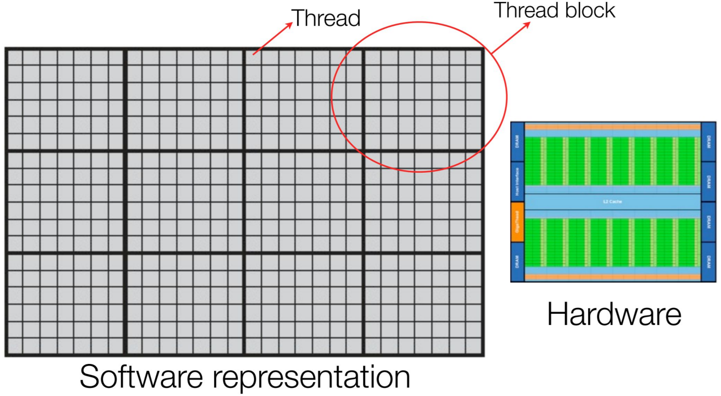
Abstractions

- CUDA (Compute Unified Device Architecture) is **both** the platform and the programming model built by NVIDIA for developing applications on NVIDIA GPUs cards.

- CUDA exposes an abstract view of the GPU parallel architecture.

- CUDA proposes 3 key logical abstractions :
  - Threads
  - Thread blocks
  - Grids





Source : NVIDIA

CUDA Execution Model (2)

Scheduling

Notion : A warp (a block of 32 consecutive threads) is the basic unit for scheduling work inside an SM.

We have two-level of scheduling provided by:

1. **The GigaThread scheduler (global scheduling):**
   - Each SM can be scheduled to run one or more thread blocks, depending on **how many resident threads and thread blocks an SM can support**. **No guarantee of order of execution.**
2. **The SM warp schedulers (local scheduling) :**
   - The warp schedulers on an SM select **active warps** on every clock cycle and dispatch them to execution units.

Outline

State-of-art

on Power Analysis

- **[Collange2009]** characterize power consumption of various GPU functional blocks (ALU, register file or memory) with real measurements on different NVIDIA GPUs.
- **[Huang2009]** propose an empirical study of the performance, the power and energy characteristics of GPUs for a GEM applications.
- **[Cebri'n2012]** analyze kernels taken from the CUDA SDK in order to discover resource underutilization.
- **[Burtscher2014]** discuss unexpected behaviors when measuring GPU power consumption, when working with k20 power samples.

Our Macroscopic Approach

- For a selected representative kernel **vector addition** , we did real measurements of the execution time and the power consumption of all phases in our code.
- Our methodology seeks to explore the execution configurations (data size, Number of threads/block, Number of Active SMs) and characterize their impact on the time and power of a compute kernel.
- This generates 3 study cases:

1. **Data size impact**
2. **Number of Threads/ Block impact**
3. **Number of blocks and Active SMs impact**

Experimental Setup

- In this work, we rely on the the **Grid'5000* infrastructure** in particular on the **Orion cluster (Lyon)**, due to the availability of a GPU card and wattmeters.
- The orion node : 2 Intel Xeon E5-2630 with 6 physical cores per CPU, 32 GiB of RAM and an **NVIDIA Tesla M2075 GPU** (fermi architecture) card (installed in 2012).
- Idle power of the node (CPU+GPU): **156 W** (subtracted in the following) : **Idle power of the targeted GPU : 57W**

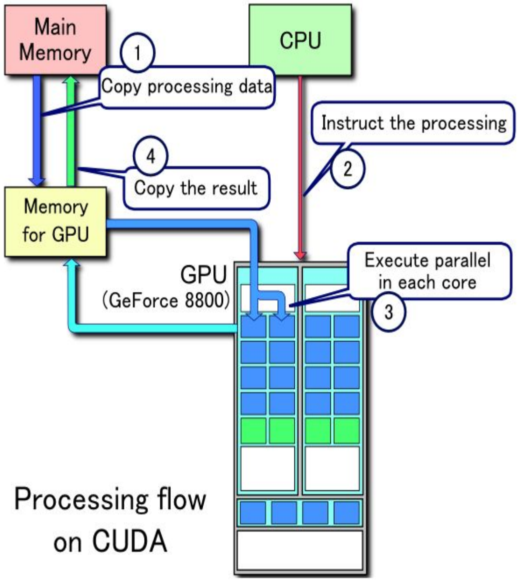
Resources	Constraints
Number of SMs	14
Number of cores/SM	32
Number of cores	448
Max Number of threads/SM	1536
Max number of threads/block	1024
Warp size	32
Global memory size	5301 Mbytes
Shared memory/Block	49152 bytes
Registers/Block	32768
Memory bus width	384-bit
Compute capability	2.0

Table1: Tesla M2075 description

*: https:// www.grid5000.fr

Vector Addition execution flow :

1. Allocates arrays in the CPU memory **(Malloc)**
2. Initiates them with random floats.
3. Allocates arrays in the GPU memory **(cudaMalloc)**
4. Copies those arrays from the CPU memory to the GPU memory **(CopyC2G)**
5. Launches the kernel by the CPU to be executed on the GPU **(VectAdd)**
6. Copies the result from the GPU memory to the CPU memory **(CopyG2C)**
7. Frees arrays from the GPU memory **(CudaFree)**
8. Frees arrays from the CPU memory **(Free)**



Case study 1: data size impact

- We use **1024 threads/block**= maximum.
- We vary the data size from 5*10^5 to 5*10^7

	Malloc(C)	Malloc(G)	CopyC2G	AddVec(G)	CopyG2C	Free(G)	Free(C)
N=500000	0.012	2218,67	1.664	23880.14	1.73	0.289	0.381
N=5000000	0.011	2216.51	12.768	235425.28	14.85	0.345	2.599
N=50000000	0.012	2216.95	123.75	2368287	144.216	0.613	22.921

Table 2: Execution time characterization in milliseconds

	Malloc(C)	Malloc(G)	CopyC2G	AddVec(G)	CopyG2C	Free(G)	Free(C)
N=500000	-	37.9	-	146.9	-	-	-
N=5000000	-	37.2	-	146.5	-	-	-
N=50000000	-	41.2	-	146,7	-	-	-

Table 3: Dynamic power consumption characterization in Average Watt

➔ **No impact on power consumption for the kernel execution.**

Case study 2: number of Threads/block impact

- For a longer run time, we used a constant data size **N=5*10^6.**
- We vary the number of threads per block (multiple of 32) from 128 to max 1024.

	Malloc(C)	Malloc(G)	CopyC2G	AddVec(G)	CopyG2C	Free(G)	Free(C)
T/B= 128	0.01	2217.81	12.80	234380.4	14.60	0.35	2.43
T/B= 256	0.01	2214.74	12.76	233362.03	14.82	0.36	2.76
T/B= 512	0.01	2214.60	12.77	242002.4	14.64	0.32	2.53
T/B= 1024	0.01	2214.65	12.92	235320.53	14.28	0.34	2.59

Table 4: Execution time characterization in milliseconds

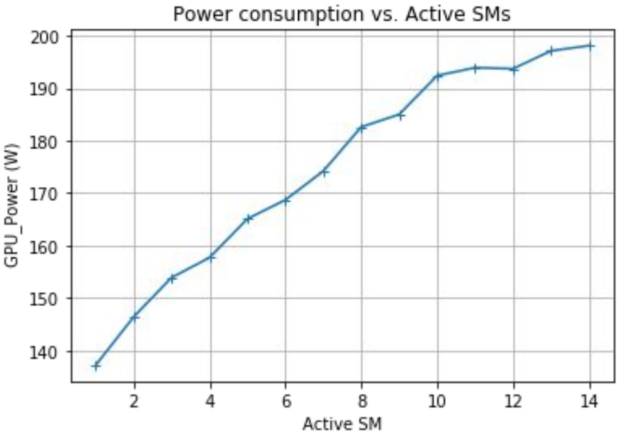
	Malloc(C)	Malloc(G)	CopyC2G	AddVec(G)	CopyG2C	Free(G)	Free(C)
T/B= 128	-	44.3	-	141.6	-	-	
T/B= 256	-	31.5	-	150	-	-	-
T/B= 512	-	39.8	-	153.3	-	-	-
T/B= 1024	-	39.4	-	142	-	-	-

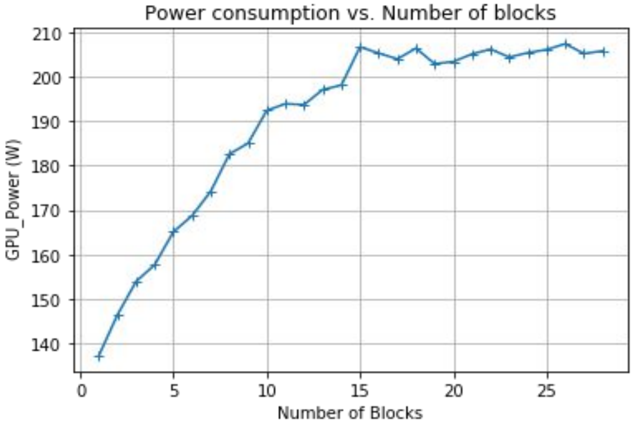
Table 5: Dynamic power consumption characterization in Average watt

➔ **A slight impact on the execution time and the dynamic power consumption.**
➔ **keeping the GPU busy, does not increase the power consumption further.**
➔ **Focus on the energy consumption and the energy efficiency !**

Case study 3: number of blocks & Active SMs impact

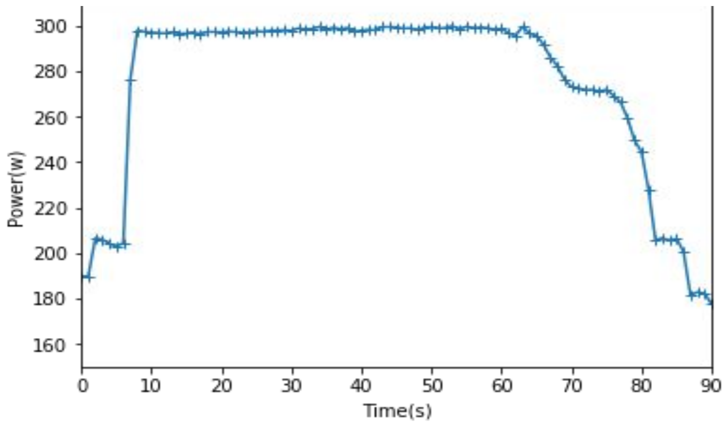
- We vary the number of active multiprocessors from 1 to the maximum (for Tesla M2075, 14 SMs).
- Indeed, we vary the number of blocks such that only one block can be executed in each SM.





Conclusions & Future works

- Investigate the irregular behavior in the power profile when having 14 blocks distributed to 14 SMs, more precisely the scheduling process proposed by NVIDIA.



Power profiling with 14 blocks

Outline

1. **Introduction**
2. **Context: GPU architecture & CUDA execution model**
3. **Our macroscopic analysis of GPU power consumption**
    a. State-of-art on GPU Power Analysis
    b. Our Methodology
    c. Experimental results & Analysis
4. **Simulating the power consumption of High Performance GPU-based Applications with SimGrid**
    a. State-of-art on GPU Power Modeling
    b. Our proposition: Fom SimGrid to GPUSimGreen
5. **Conclusion & Future works**

State-of-art (1)

GPU Power models and Simulators

- **[Sheaffer2005]** propose a functional performance, power and temperature simulator: **Qsilver**: the first microarchitectural simulator for GPUs.
- **[Lucas2013]** and **[Leng2013]** propose respectively **GPUSimPow** and **GPUWattch**. Two power models build on the GPU performance simulator **GPGPU-Sim.** Both models rely on the **McPAT** tool to model GPU microarchitectural components.

Limitations:

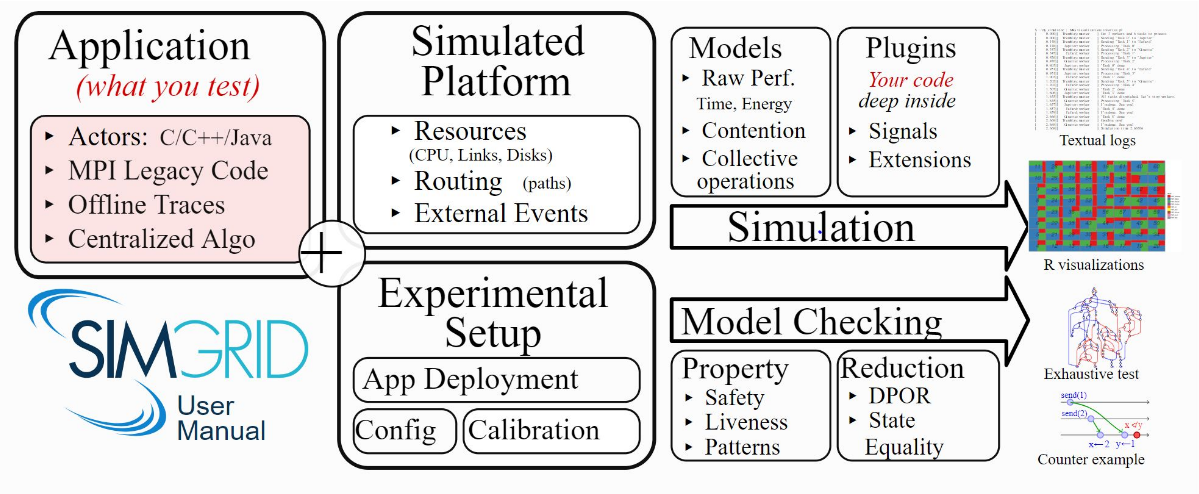
- Such models require a deep knowledge of the architecture.
- GPU architecture is evolving very fast.
- Detailed product specifications are not usually public.

Our Proposition

- A GPU power model that is simpler, more flexible and portable through different generations of GPUs.
- **Simulation is an excellent approach to study HPC applications behavior in time and power.**
- Our proposition is then to simulate the performance and power consumption of HPC applications for GPUs using an open-source toolkit SimGrid.
- Inspiration : work done by **[Heinrich2017]** for CPUs in SimGrid.

Why SimGrid ?
How simulate it inside ?

- A free scientific tool for simulating different distributed systems such as grids, clouds, HPC or P2P systems = **reproducible**
- Provides accurate yet **fast** simulation models.
- Offers off-line and on-line simulation.

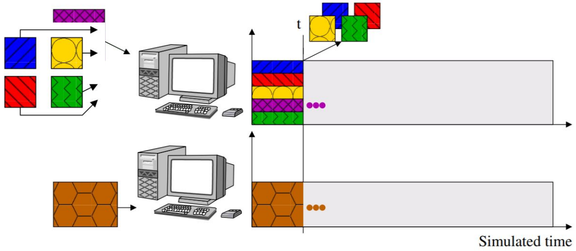


How CPU is modeled ?
What we propose for GPUs ?

GPUSimGreen

CPU model in SimGrid

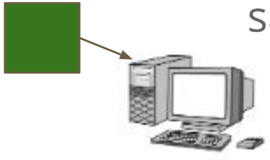
- Computational resources: cores with capacity C (Flops).
- Resource sharing algorithm
- Power is a linear to CPU usage

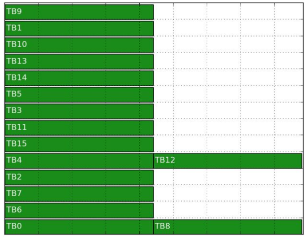


Source: SimGrid tutorial

Our GPU model in SimGrid

- Computational resources: SMs with capacity C (Flops) as a black box
- Round Robin algorithm (as Nvidia says) on blocks !!





Source: https://users.ices.utexas.edu/~sreepai/fermi-tbs/

On going (slowly but surely..)

- Developing our GPU performance and power models in SimGrid.
- Validating our model with real measurements of applications from the SHOC benchmark suite, NAS, and machine learning applications.
- Extend our power model to support GPU DVFS in SimGrid.

Thank you for your attention !

Questions ?

References

- **[Top500] :** Top500 website, URL = https://www.top500.org/
- **[Green500] :** online, URL = https://www.top500.org/green500/
- **[Collange2009] : "**Power consumption from a software perspective", in International Conference on computational Science, 2009
- **[Huang2009]:** " On the energy efficiency of graphics processing units for scientific coomputing", IPDPS 2009
- **[Cebri'n2012]:** " Energy efficiency analysis of GPUs", International Parallel and Distributed Processing symposium workshops PhD forums",2012
- **[Burtscher204]:** "Measuring GPU power with k20 built-in-sensor", GPGPU-7,2014
- **[Sheaffer2005]:** "Fine-grained graphics architectural simulation with Qsilver", ACM SIGGRAPH, 2005
- **[Lucas2013]:** " How a single chip causes massive power bills ? GPUSimPow: A GPGPU power simulator", ISPASS, 2013
- **[Leng2013]:** "GPUWattch: Enabling energy optimizations in GPGPUs, ISCA, 2013
- **[Heinrich2017]:** "Predicting the energy consumption of MPI applications at scale using a single node", CLUSTER, 2017

How CPU power is modeled in SimGrid ?

```
<host id="MyHost2" speed="100.0Mf" >
   <prop id="watt_per_state" value="100.0:200.0" />
   <prop id="watt_off" value="10" />
</host>
```

- The power consumption is a **linear function** of the CPU usage (proved by real experiments).
- For this example, 100W is the idle power, and 200W is the power when the CPU is fully loaded.
- So when the CPU is 50% , we have 150W

State-of-art (1)

GPU counter-based Power models

$$Power = Dynamic_{power} + Static_{power}.$$

Method	Device	Year
SVR	Nvidia 8800GT	2009
SLR	Nvidia Tesla GTX285	2010
RF	AMD Radeon HD5870 /Tesla CTX280	2011
ANN	Nvidia fermi C2075	2013
K-means	AMD Radeon HD7970	2015

- Rely on performance counters to yield correlation to power consumption
- Methods used are linear (like SLR support linear regression etc,) or non-linear (RF random forest, ANN artificial neural network, K-means etc,)
- **Limitations:**

- The number and type of counters are not uniform across hardware.
- Some architectures only allow counters for a whole SM.