Power and Performance Analysis of GPU-Accelerated Systems

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Abstract

Graphics processing units (GPUs) provide significant improvements in performance and performance-per-watt as compared to traditional multicore CPUs. This energy-efficiency of GPUs has facilitated the use of GPUs in many application domains. Albeit energy efficient, GPUs consume non-trivial power independently of CPUs. Therefore, we need to analyze the power and performance characteristic of GPUs and their causal relation with CPUs in order to reduce the total energy consumption of the system while sustaining high performance. In this paper, we provide a power and performance analysis of GPU-accelerated systems for better understandings of these implications. Our analysis on a real system discloses that system energy can be reduced by 28% retaining a decrease in performance within 1% by controlling the voltage and frequency levels of GPUs. We show that energy savings can be achieved when GPU core and memory clock frequencies are appropriately scaled considering the workload characteristics. Another interesting finding is that voltage and frequency scaling of CPUs is trivial for total system energy reduction, and even should not be applied in state-of-the-art GPU-accelerated systems. We believe that these findings are useful to develop dynamic voltage and frequency scaling (DVFS) algorithms for GPU-accelerated systems.

1 Introduction

Graphics processing units (GPUs) have been increasingly deployed in general-purpose application domains due to their significant improvements in performance and performance-per-watt. As depicted in Figure 1, the performance-per-watt of GPUs highly outperforms that of traditional multicore CPUs. Albeit energy efficient, GPUs consume non-trivial power during operation. However, commodity system software for GPUs is not well designed to control their power consumption while primarily tailored to accelerate computations. To the best of our knowledge, commodity system software does not employ any voltage and frequency scaling for GPUs, while most computational pieces of GPU-accelerated systems are offloaded on to GPUs. In order to develop energy-efficient GPU-accelerated systems, it is essential to identify the trade-off in power and performance of GPUs and its causal relation with CPUs.

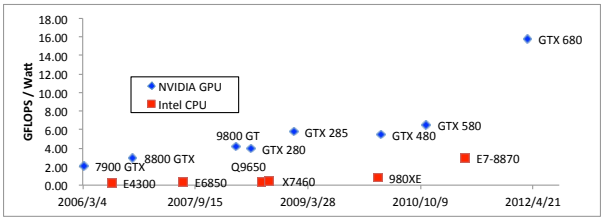


Figure 1: Performance-per-watt trends on representative NVIDIA GPUs [11] and Intel CPUs [6].

Despite rapid growth of GPU technology, there has not been much understanding of power and performance implications of GPU-accelerated systems. According to vendor's specifications, thermal design power (TDP) of state-of-the-art GPUs is around 200W, while that of today's multicore CPUs is typically below 100W. Because TDP of GPUs is comparable to or even higher than that of CPUs, it is hard for system designers to optimize their energy savings by predicting the power and performance of GPU-accelerated systems without understandings of GPU power-performance characteristics. However, previous work [4, 3, 7, 9, 10] on the power and performance analysis of GPU-accelerated systems are based on either simulation studies or limited hardware functionality. None of previous work has ever disclosed a fundamental approach to the power and

The contribution of this paper is to provide a power and performance analysis of GPU-accelerated systems using NVIDIA's Fermi architecture (GeForce GTX 480). Specifically, we identify when to scale the frequency and voltage of GPUs *and* CPUs in order to minimize overall system energy. Our analysis opens up important problems of dynamic voltage and frequency scaling (DVFS) algorithms for growing GPU-accelerated systems. We also provide an open method and tool to scale voltage

Table 1: Performance levels of GTX 480 (GPU)

Clock Domains	Min [MHz]	Low [MHz]	High [MHz]
Core	50	405	700
Memory	135	324	1848

Table 2: Performance levels of Core i5 2400 (CPU)

Platforms	Min [MHz]	Low [MHz]	High [MHz]
Core i5-2400	1600	2700	3300.1

and frequency of GPUs. The black box feature of current GPU drivers and runtimes prevents researchers from tackling correlative power and performance optimization problems. We believe that sharing such a common method and tool with researchers would further facilitate the use of GPUs.

The rest of this paper is organized as follows. Section 2 presents our system platform and Section 3 provides evaluation results and analyses. Section 4 discusses related work, and the paper is concluded in Section 5.

2 System Platform

We use an NVIDIA GeForce GTX 480 graphics card and Intel Core i5 2400 processor with the Linux kernel 3.3.0. Tables 1 and 2 present their available performance levels, respectively. To perform the experiment, we use NVIDIA's proprietary software [13] and Gdev [8] on a case by case basis. NVIDIA's proprietary software does not provide a system interface to scale the performance level of the GPU. We hence provide the modified BIOS files for the GPU that force the binary driver to configure the GPU with the specified performance level when loaded. This method enables us to choose any set of the GPU core and memory clocks, but requires the driver to reload, and the configuration is static while the driver is running. On the other hand, Gdev allows the system to change the performance level of the GPU dynamically at runtime through the Linux "/proc" file system interface. However, it is available only for the GPU core clock at the moment, and the GPU memory clock is fixed at 135MHz. This is limited due to an open-source implementation of Linux, but is supposed to be removed in the future release.

The experimental workload executes the Rodinia benchmark suite 2.0.1 [2] and our original microbenchmark programs of matrix computation. All input data for the Rodinia programs use the maximum feasible size, while the microbenchmark programs vary data size to conduct fine-grained measurements, all of which are written in CUDA. We use the NVIDIA CUDA Compiler (NVCC) 4.0 [12] to compile the programs. Note that both NVIDIA's proprietary software and Gdev receive the same program binary.

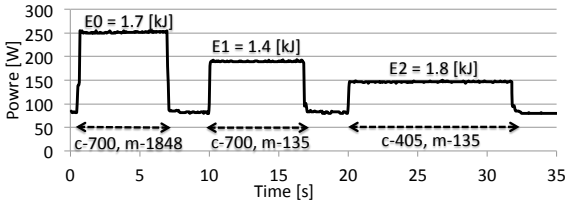


Figure 2: Power consumption and execution time of the 512×512 matrix addition program.

The power and energy consumption of the system is measured by the Yokogawa Electric Corporation's WT1600 digital power meter [1]. This instrument obtains the voltage and electric current every 50ms from the power plug of the machine. The power consumption is calculated by multiplying the voltage and current, while the energy consumption is derived by accumulation of power consumption.

3 Evaluation and Analysis

We first investigate the impact of GPU core and memory clocks on GPU-intensive workload executing 20,000 loops of 512×512 matrix addition. The voltage and frequency of the GPU is changed three times during the operation, while that of the CPU is fixed at the minimum level to focus on the behavior of the GPU. Figure 2 shows the power consumption of the system in this setup, where "c-*" and "m-*" stand for the GPU core and memory clocks, respectively, while "E*" represents the cumulative energy consumption of the corresponding duration. What is learned from this experiment is that it is important to cooperatively scale the GPU core and memory clocks to effectively reduce energy consumption. Lowering the memory clock to 135MHz successfully reduces energy consumption, but the downscaling of the core clock to 405MHz counter-increases energy consumption. This indeed implies DVFS algorithms dominate the power and performance of GPU-accelerated systems.

We next coordinate the GPU and the CPU using more realistic workload from the Rodinia benchmark suite. To simplify the setup, we consider only high and low core clocks, meaning that we evaluate four configurations of (GPU-L, CPU-L), (GPU-H, CPU-L), (GPU-L, CPU-H) and (GPU-H, CPU-H), where "*-L" and "*-H" represent the low and high core clocks. The GPU memory clock is fixed at 135MHz. In an idle state, however, the clocks are always down-scaled to the minimum level. We also add another configuration (all-H) that keeps at the maximum clocks even though the GPU is idle, in order to see the impact of elementary coordinated DVFS on GPU-accelerated systems. Figures 3 and 4 respectively

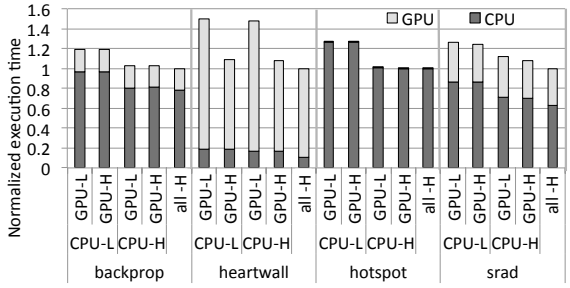


Figure 3: Execution time of the Rodinia programs.

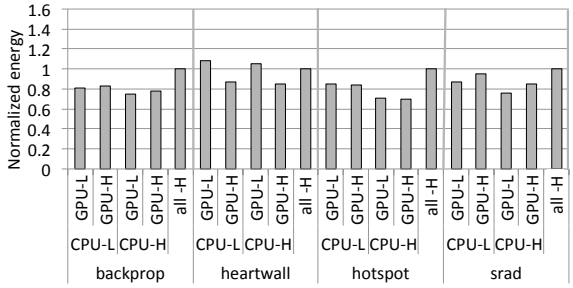


Figure 4: Energy consumption of the Rodinia programs.

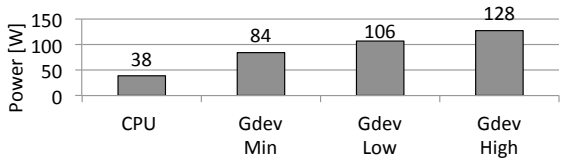


Figure 5: Power consumption in an idle state.

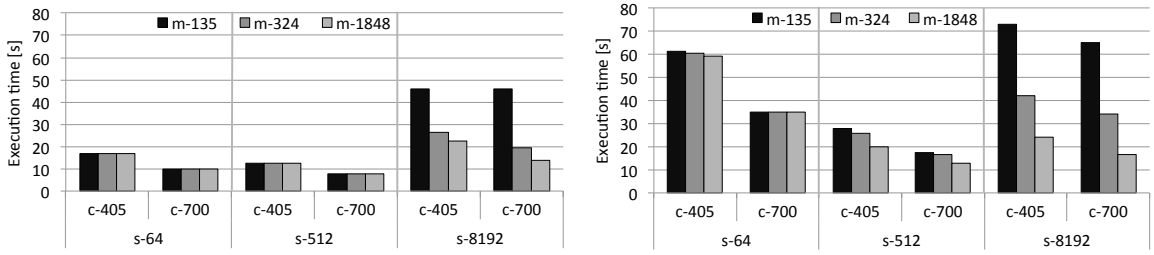
show the execution time and energy consumption of four representative programs of the Rodinia benchmark suite. Regarding the execution time, "all-H" always takes the shortest execution time, as it consistently keeps at the maximum performance level. Other configurations however depend on workload. For example, the execution time of `heartwall` – GPU-intensive workload – can be decreased by setting the high GPU clock, whereas that of `hotspot` is rather affected by the CPU clock. The characteristics of energy consumption is more complicated. For some workload, lowering the clock causes an increase in energy consumption, as the duration of execution is increased, consuming more cumulative power consumption. In other words, GPU-intensive workload should generally use the high GPU clock so that it completes operation as soon as possible to minimize energy. Apparently, "all-H" is not a good idea in terms of energy; the clock should be minimized when the device is not used.

In the above experiments, we have never observed that energy consumption is reduced by lowering the CPU clock. This is because lowering the CPU clock causes the GPU to increase the duration of an idle state. Hence, energy is always wasted when the GPU is idle. We demonstrate how energy consumption is wasted in an idle state, when (i) the GPU is not present and (ii) is present with three levels of a set of voltage and frequency. Figure 5 shows the average power consumption of those four cases obtained by running the system for 60 seconds without performing any computations (idle state). The CPU consumes no more than 38W on average, whereas the GPU-installed systems consume a different scale of power depending on the configured set of voltage and frequency. This observation encourages the system not to downscale the voltage and frequency of the CPU, unless the idle power consumption of future GPUs becomes small enough by hardware optimization techniques. The lesson learned from this experiment is that the power consumption of the GPU is significant even in an idle state, meaning that DVFS is strongly desired for the GPU with whatever overhead it has to pay for changing the performance level.

The preceding evaluation indicates that the CPU is a weak factor for energy savings of GPU-accelerated systems. Henceforth, we restrict our attention to the GPU. According to the traditional power modeling [5], lowering the core clock is often effective for memory-intensive workload. Our next evaluation verifies whether the same is true for the GPU. We use matrix addition and multiplication programs with varied sizes of data. A small size of data reduces memory accesses, while a large size of data makes the workload memory-intensive. Figures 6 and 7 show the execution time and energy consumption of those matrix computations, where "s-*" represents the number of matrix row/column. A difference between "s-64" and "s-8192" in Figure 7 shows that memory-clock scaling is more effective for such computations that use a smaller size of data. This is because the execution time of such computations is not affected by lowering the memory clock. Another observation is that energy cannot be saved by lowering the core clock, because these matrix computations are consistently compute-intensive. If the core clock is downscaled, their execution time is highly increased, which results in an increase in cumulative power consumption.

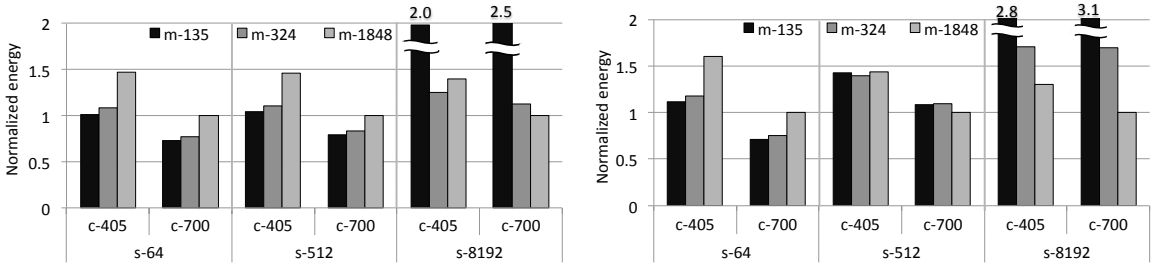
Seen from the above experiments, system energy could be reduced by about 28% retaining a decrease in performance within 1%. These experimental results encourage that DVFS algorithms for GPU-accelerated systems should be weighted on the GPU rather than the CPU, though their energy optimization is very challenging, given many factors of design knobs including CPU/GPU, core/memory, and workload characteristics.

Finally, we compare NVIDIA's proprietary software and Gdev. This is an important and practical investigation because NVIDIA's proprietary software does not expose a system interface to change the voltage and frequency of the GPU dynamically at runtime, and hence



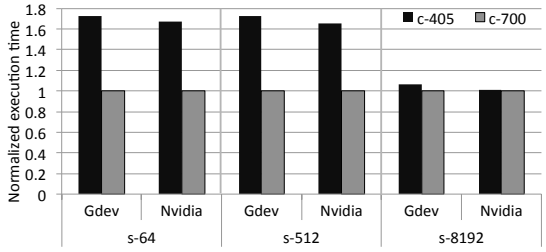
(a) `Matrix Addition` (b) `Matrix Multiplication`

Figure 6: Execution time of the matrix addition and multiplication programs.

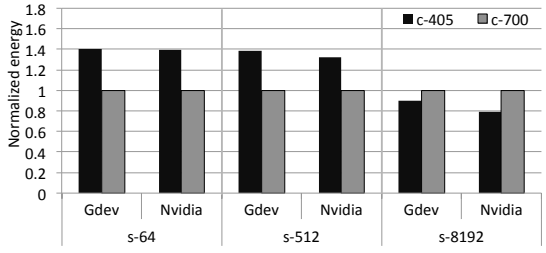


(a) `Matrix Addition` (b) `Matrix Multiplication`

Figure 7: Energy consumption of the matrix addition and multiplication programs.



(a) `Execution Time`



(b) `Energy Consumption`

Figure 8: Comparison of the NVIDIA proprietary and the Gdev open-source runtimes and drivers.

the development of DVFS algorithms in future work will inevitably depend on Gdev. The basic performance of Gdev is competitive to NVIDIA's proprietary software [8], but we have to evince that Gdev is also reliable for power management. The test program exploits matrix addition with varied sizes of data. Figure 8 shows the execution time and energy consumption of the matrix addition programs using different scales of GPU core clocks, where the GPU memory clock is fixed at 135MHz. In this experiment, "s-8192" benefits from lowering the core clock, because the workload is memory-bound due to a large size of matrix, and the execution time is not much affected by the core clock, while energy is effectively saved. The most remarkable observation is that NVIDIA's proprietary software and Gdev exhibit almost the same results on the execution time and energy consumption. This implies that the result of our on-going research using Gdev could be easily propagated to the real product, once energy management interfaces are employed by vendor's software. Note that tools and documentations for the power and performance management of the GPU may be downloaded from our website.[1]

[1] http://sys.ertl.jp/gdev/

4 Related Work

Nagasaka *et al.* conjectured energy consumption of GPUs based on hardware performance counters [10]. Their model is not adequate in that we have seen that power consumption rises even in an idle state when voltage and frequency are scaled, though they do not consider it. Hence, this approach would require an additional model to precisely analyze the power consumption of GPUs.

Hong *et al.* studied energy savings of GPUs, assuming power gating available to limit the number of active cores [3, 4]. In particular, they analyze PTX code to model the power and performance of GPUs based on the number of instructions and memory accesses. We consider that an offline PTX analysis for power and performance prediction is a useful approach to the design of DVFS algorithms. What lacks in this approach, however, is a runtime analysis for input data. In this paper, we have analyzed the power and performance characteristics depending on the size of input data.

Lee *et al.* presented a method to apply DVFS algorithms to the GPU. They particularly aimed at maximizing performance under the given power constraint [9]. A strong limitation of their work, however, is that the evaluation of power consumption is based on a conceptual model but not on real-world hardware. They also failed to discuss how to determine the voltage and frequency. In this paper, we have rather explored how to minimize the energy consumption of GPU-accelerated systems using the cutting-edge real-world hardware.

Jiao *et al.* evaluated the power and performance of an old NVIDIA GTX 280 GPU [7]. They examined compute-intensive and memory-intensive programs. According to their analysis, energy consumption could often be reduced by lowering the core clock when workload is memory-intensive. This is exactly the same as what we have identified for an NVIDIA's GTX 480 GPU. Therefore, we conjecture that this observation and knowledge could be applied to future GPU architectures as well. In addition, we have disclosed that energy consumption could also be reduced by scaling the memory clock. This opens up a new insight into DVFS algorithms for GPU-accelerated systems.

Ying *et al.* analyzed the power and performance of an AMD HD 5870 GPU using a random forest method with the profile counter [14]. They revealed that activating a fewer number of ALUs reduces power consumption. However, this approach incurs an increase in execution time, and does not successfully reduce energy consumption. This is attributed to the fact that they use only software management. Meanwhile, we have demonstrated that energy can be reduced by scaling the voltage and frequency of the GPU.

5 Conclusion and Future Work

We have presented a power and performance analysis of GPU-accelerated systems based on the NVIDIA Fermi architecture. Our findings include that the CPU is a weak factor for energy savings of GPU-accelerated systems unless power gating is supported by the GPU. In contrast, voltage and frequency scaling of the GPU is significant to reduce energy consumption. Our experimental results demonstrated that system energy could be reduced by about 28% retaining a decrease in performance within 1%, if the performance level of the GPU can be scaled effectively.

In future work, we plan to develop DVFS algorithms for GPU-accelerated systems, using the characteristic identified in this paper. We basically consider such an approach that controls the GPU core clock for memory-intensive workload while controls the GPU memory clock for compute-intensive workload. To this end, we integrate PTX code analysis [3, 4] into DVFS algorithms so that energy optimization can be provided at runtime. We also consider a further dynamic scheme that scales the performance level of the GPU during the execution of GPU code, whereas we restricted a scaling point at the boundary of GPU code in this paper.

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