Cuttlefish: Library for Achieving Energy Efficiency in Multicore Parallel Programs

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A low-cap power budget is challenging for exascale computing. Dynamic Voltage and Frequency Scaling (DVFS) and Uncore Frequency Scaling (UFS) are the two widely used techniques for limiting the HPC application’s energy footprint. However, existing approaches fail to provide a unified solution that can work with different types of parallel programming models and applications.

This paper proposes Cuttlefish, a programming model oblivious C/C++ library for achieving energy efficiency in multicore parallel programs running over Intel processors. An online profiler periodically profiles model-specific registers to discover a running application’s memory access pattern. Using a combination of DVFS and UFS, Cuttlefish then dynamically adapts the processor’s core and uncore frequencies, thereby improving its energy efficiency. The evaluation on a 20-core Intel Xeon processor using a set of widely used OpenMP benchmarks, consisting of several irregular-tasking and work-sharing pragmas, achieves geometric mean energy savings of 19.4% with a 3.6% slowdown.

CCS Concepts: • Software and its engineering → Power management.
Additional Key Words and Phrases: Multicore parallelism, DVFS, UFS, energy efficiency

1 INTRODUCTION

The current generation of supercomputers is composed of highly multicore processors. The ever-increasing core counts are likely to continue in the present and post-Exascale ($10^{18}$ flops/sec) era. The Top500 list for November 2020 shows 50% of supercomputers have 20–24 cores per socket, and the fastest supercomputer, Fugaku, has 48 cores [2]. Limiting power consumption is one of the significant challenges today. For an exascale system to be delivered within a power budget of 20–30 MW [33], the hardware and software components need to be highly energy-efficient.

Cache-coherent shared memory processors that dominate modern high-performance computing (HPC) systems contain multiple levels of caches in each socket. Most processor architectures are a combination of core and uncore elements. The uncore includes all chip components outside the CPU core [21], such as shared caches, memory controllers, and interconnects (QPI on Intel platforms). The processor power consumption can be regulated using multiple knobs for such as Dynamic Voltage and Frequency Scaling (DVFS) [28] and Dynamic Duty-Cycle Modulation (DDCM) [24] for CPU cores, and Uncore Frequency Scaling (UFS) [21] for the uncore. DVFS allows scaling down the core’s voltage and frequency, thereby reducing power consumption as lowering the voltage has a squared effect on active power consumption. The static losses have become significant with transistor shrinkage, undermining the previously achievable power savings with DVFS [15]. Nevertheless, DVFS is still the most effective and widely used power control.

Most energy-efficient HPC research has revolved around reducing the processor/core frequency by using DVFS or DDCM with minimum performance impact (see Section 6). These implementations adapt the core frequencies as follows: a) based on trace data collected from the application’s offline profiling, b) whenever parallel programs encounter slack time due to unbalanced computation or inter-node communication delays, c) gathering workload characteristics by profiling iterative and
loop-based applications, and d) programming model and runtime-dependent application profiling. A standard limitation of these studies is that they are specific to a particular application or programming model. Recently, UFS has been explored for achieving energy efficiency based on machine learning models on offline generated application data [3] and by dynamically profiling the DRAM power consumption [18]. However, these studies lack an integrated approach for core and uncore frequency scaling.

This paper explores a one-stop solution for achieving energy efficiency on multicore processors called Cuttlefish that dynamically adapts both the core and uncore frequencies on Intel processors without requiring training runs. Cuttlefish is oblivious to the parallel programming model and the concurrency decomposition techniques used in an application. In their application, programmers only need to use two API functions, cuttlefish::start() and cuttlefish::stop(), to define the scope requiring an energy-efficient execution. At runtime, Cuttlefish then creates a daemon thread that periodically profiles the application’s Memory Access Pattern (MAP) by reading the Model-Specific Registers (MSR) available on all Intel platforms. Each MAP is uniquely identified as the ratio of uncore event TOR_INSERT [25] and instructions retired. Cuttlefish daemon then uses DVFS to determine the core frequency that would provide maximum energy savings with minimal impact on execution time. After finding and setting this optimal core frequency, Cuttlefish daemon then uses the same exploration-based technique to determine the optimal uncore frequency. To reduce the loss in performance, it uses several runtime optimizations to complete the frequency explorations quickly. Once both optimal core and uncore frequencies are found for a given MAP, the rest of the program would execute at these frequencies. Cuttlefish would repeat this frequency exploration for core and uncore every time a new MAP is discovered. We chose a set of ten widely-used OpenMP benchmarks, consisting of several irregular-tasking and work-sharing pragmas to evaluate Cuttlefish on a 20-core Intel processor. We show that Cuttlefish significantly improves the energy-efficiency with a negligible impact on performance. We also evaluated Cuttlefish by implementing a subset of these benchmarks using async–finish task parallelism [30] to demonstrate that Cuttlefish is oblivious to the parallel programming model.

In summary, this paper makes the following contributions:

- Cuttlefish, a parallel programming model oblivious C/C++ library for achieving energy efficiency in multicore parallel programs running on Intel processors.
- A novel light-weight runtime for Cuttlefish that periodically monitors the memory access pattern of a running application and then dynamically adapts the core and uncore frequencies using DVFS and UFS, respectively.
- Evaluation of Cuttlefish on a 20-core Intel Xeon Haswell E5-2650 processor by using multiple HPC benchmarks and mini-applications implemented in OpenMP and async–finish programming model. Our evaluation shows that Cuttlefish can significantly improve energy efficiency with negligible impact on the execution time for several irregular-tasking and work-sharing pragmas.

2 EXPERIMENTAL METHODOLOGY

Before presenting the motivating analysis for Cuttlefish, we first describe our experimental methodology. To cover a broad spectrum of parallel applications, we have chosen benchmarks based on the following attributes: a) memory access patterns, b) micro-kernels and real-world mini-applications, c) execution DAG, and d) concurrency decomposition techniques. We target six widely-used benchmarks for our experimental evaluation. These benchmarks mainly use OpenMP pragmas, but a few were ported to async–finish programming model supported by the HClib work-stealing library [19, 30] to evaluate Cuttlefish using two different parallel programming models. We created
| Benchmark Name | Brief Description | Configuration | Parallelism Style | OpenMP Time (sec) | TIPI Range | Total TIPI Slabs |
|----------------|------------------|---------------|-------------------|-------------------|-------------|-----------------|
| UTS            | Unbalanced Tree Search [36] | TIXXL       | Irregular Tasks   | 69.9              | 0.004-0.004 | 1               |
| SOR-irt        | Successive Over-Relaxation (SOR) [7] | 32Kx32K (200) | Irregular Tasks   | 69.1              | 0.024-0.028 | 1               |
| SOR-rt         | ___________________ |             | Work-sharing      | 69.4              | 0.024-0.028 | 1               |
| SOR-ws         | ___________________ |             | Regular Tasks     | 69.4              | 0.024-0.028 | 1               |
| Heat-irt       | Heat diffusion (Jacobi-type iteration) [35] | 32Kx32K (200) | Irregular Tasks   | 76.6              | 0.056-0.076 | 1               |
| Heat-rt        | ___________________ |             | Work-sharing      | 75.5              | 0.056-0.072 | 3               |
| Heat-ws        | ___________________ |             | Regular Tasks     | 75.5              | 0.056-0.072 | 3               |
| MiniFE         | Finite Element Mini-Application [1, 11] | 256x512x256 (200) | Work-sharing      | 78.5              | 0.060-0.152 | 16              |
| HPCCG          | High Performance Computing Conjugate Gradients [1, 11] | 256x256x1024 (149) | Work-sharing      | 70.0              | 0.012-0.068 | 11              |
| AMG            | Algebraic Multigrid solver [32] | 256x256x1024 (22) | Work-sharing      | 63.7              | 0.060-0.332 | 60              |

Table 1. Description of the benchmarks used in this paper for the evaluation of Cuttlefish

Fig. 1. Heat-irt and SOR-irt use the irregular execution DAG, whereas Heat-rt and SOR-rt use the regular execution DAG. Non-root and non-leaf grey and black nodes have degrees three and five, respectively. Each node is parallel task.

three variants (both for OpenMP and HClib) that differ in execution DAG and concurrency decomposition technique for two of these benchmarks, Heat and SOR. Two of these variants use dynamic task parallelism and vary in terms of irregular (irt) and regular (rt) execution DAGs. The third variant is a non-recursive implementation that uses work-sharing (ws) based static loop partitioning. The technique described in Chen et al. [8] was used for converting the loop-level parallelism in Heat and SOR into regular and irregular execution DAG, as shown in Figure 1. In total, we have ten benchmarks mini-applications. Table 1 describes them and their respective configurations.

We ran all experiments on an Intel Xeon Haswell E5-2650 v3 20-core processor with a total of 94GB of RAM. The operating system (OS) was Ubuntu 16.04.7 LTS. This processor supports core and uncore frequencies between 1.2GHz–2.3GHz and 1.2GHz–3.0GHz, respectively, both in steps 0.1GHz. We used MSR–SAFE [34] for saving and restoring Model-Specific-Register (MSR) values. The turbo boost feature on the processor was disabled, and each benchmark used interleaved memory allocation policies supported by the numactl library. The HClib implementation from the official Github repository with the commit id ab310a0 is used. Both OpenMP and HClib versions of the benchmarks used the Clang compiler version 3.8.0 with the -O3 flag. All 20 threads used in the experiments were bound to their respective physical CPUs. Although we use an Intel Haswell processor in our evaluation, more recent Intel processors can use Cuttlefish by updating the MSRs specific to them. While the latest AMD processors do support per-core DVFS similar to Intel, based on public documentation available, it is not clear if support for UFS or TIPI measurement exists.

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We evaluated three variants of Cuttlefish: a) Cuttlefish-Core that only adapts the CPU frequency, b) Cuttlefish-Uncore that only adapts the Uncore frequency, and c) Cuttlefish that adapts both the CPU and Uncore frequencies. We compared these implementations against each benchmark’s Default execution by setting the Intel power governor to performance policy. The performance power governor fixes the CPU frequency to the maximum. We chose performance power governor for Default execution as this same setting is used by several supercomputers in production [10, 20]. For Cuttlefish-based executions, the power governor is set to userspace to allow changes to the CPU frequency through the library. We changed the uncore frequency scaling option to Auto in the BIOS, allowing the Intel firmware to modulate the uncore frequency during the Default execution.

The algorithm used by Intel is highly sensitive to memory requests. During Cuttlefish executions, the runtime controls the uncore frequency dynamically inside the library by writing the desired frequency value in the UFS MSR (0x620). We executed each implementation ten times and reported the mean value along with a 95% confidence interval.

3 MOTIVATING ANALYSIS

(a) Variation in JPI during the course of execution

(b) Variation in TIPI during the course of execution

Fig. 2. Relation between TIPI and JPI. For each benchmark, JPI increases with the increase in TIPI

An application’s memory access pattern (MAP) can be primarily classified as memory-bound or compute-bound. Memory-bound applications have a high number of memory accesses as compared to compute-bound applications. This section presents two analyses to support that MAP of an application can be accurately identified using MSRs (Section 3.1), and changing the core and uncore frequencies based on MAP can lead to energy savings (Section 3.2).

3.1 TOR Inserts per Instruction (TIPI)
To accurately identify the MAP of an application, we propose the metric TOR Inserts per Instruction (TIPI), which is calculated as the ratio of total TOR Inserts (TOR_INSERT.MISS_LOCAL + TOR_INSERT.MISS_REMOTE) and total instructions retired (INST_RETIRED.ANY). Any requests coming to the LLC from the processor cores are placed in TOR (Table of Request). TOR_INSERT MSR [25] is available on all Intel processors from Haswell generation and onwards. This MSR counts the number of memory requests that come to the socket-specific Last-Level Cache (LLC) from each core. It supports various Unit Masks (umask) to select the type of memory requests to be counted. MISS_LOCAL counts the misses to the local caches and memory, and MISS_REMOTE counts the misses to the remote caches and memory as per the Intel documentation [25]. We consider both these umasks as our experimental machine is a two-socket NUMA machine (Section 2). The other metric used is Joules per Instructions (JPI). JPI is calculated as the ratio of the total energy spent by the processor and the total instructions retired. The package energy is measured using the Intel RAPL MSRs.

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We found that compute-bound and memory-bound applications have low and high TIPI values, respectively. It is also observed that TIPI has a strong correlation with JPI as an increase in TIPI also increases the JPI. These observations are reported in Figure 2. The core and uncore frequencies are initially set to the maximum, and periodically the TIPI and JPI for an application is recorded at every $T_{inv}$ intervals. The $T_{inv}$ is fixed at 20 milliseconds and is empirically derived for all experiments reported in this paper. The x-axis in Figure 2 represents the execution timeline of each benchmark in seconds. The y-axis in Figure 2(b) and Figure 2(a) shows the TIPI and JPI, respectively, during the benchmark’s execution. The result of only Heat-irt and SOR-irt are reported as their variants have similar behaviours. As JPI is highly sensitive to TIPI, JPI is used to measure energy efficiency for a given TIPI. In Figure 2(a), SOR-irt has a higher JPI than Heat-irt, although SOR-irt’s TIPI is less than that of Heat-irt (Figure 2(b)). For MiniFE, HPCCG, and AMG, it is observed that TIPI varies throughout the execution. However, an increase in TIPI shows an increase in JPI. This implies that the TIPI v/s JPI trend holds only within an application, and the same TIPI value could have different JPIs for different applications.

3.2 Analysis of DVFS and UFS with TIPI

Cuttlefish has an online profiler that explores optimal core and uncore frequencies for every unique TIPIs discovered during a benchmark execution. To limit the search space, we divide each unique TIPIs in fixed slabs of 0.004 (derived empirically), i.e., TIPI values 0.004, 0.005, and 0.007 would be reported under the TIPI range 0.004-0.008. Hereafter, a TIPI value is reported in terms of its range instead of the actual value. Figure 3 shows the relation between TIPI and JPI for benchmarks at different core and uncore frequencies. In Figure 3(a), the Uncore Frequency (UF) is set to max (3.0 GHz) and each benchmark is executed with three different Core Frequencies (CF) – min (1.2 GHz), mid (1.8 GHz) and max (2.3 GHz). In Figure 3(b), the CF is set to max (2.3 GHz) and each benchmark is executed with three different UFs – min (1.2 GHz), mid (2.1 GHz) and max (3.0 GHz). In each execution of a benchmark, we record the TIPI and JPI at every $T_{inv}$ and then calculate the average.

Fig. 3. Motivational analysis to understand the effect of core and uncore frequencies on the JPI at each TIPI

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JPI for the frequently occurring TIPIs. TIPIs found in more than 10% of total T\textsubscript{inv} samplings are mentioned as frequently occurring TIPIs during an execution.

We can observe that UTS and SOR-irt have a low TIPI range and are compute-bound as their JPI decreases with increasing CF and JPI increases with increasing UF. Heat-irt, MiniFE, HPCCG, and AMG have a high TIPI range and are memory-bound applications as they behave precisely opposite to UTS and SOR-irt. JPI of these four benchmarks increases with increasing the CF, and their JPI decreases with increasing the UF. Although Heat-irt, MiniFE, HPCCG, and AMG are memory-bound, max uncore frequency is not apt for their TIPI range. This analysis implies that when TIPI is low, CPU cores should run at a higher frequency, and uncore should run at a lower frequency. In contrast, when TIPI is high, uncore should run at a higher frequency, and CPU cores should run at a lower frequency as the latter would frequently halt due to the memory access latency.

4 DESIGN AND IMPLEMENTATION

The previous section highlighted that TIPI could be used to distinguish the MAP of an application and for estimating its optimal core and uncore frequencies. Hence, to achieve energy efficiency in an application with minimal loss in performance, it is vital to use a low-overhead online profiler to discover the TIPI ranges dynamically and appropriately set the core and uncore frequencies. We approach the problem using a lightweight daemon thread, Cuttlefish, that runs in tandem with the application to monitor the TIPI and JPI by activating itself after every T\textsubscript{inv} durations to minimize the time-sharing of the CPU with the application. In their application, programmers only need to use two API functions, cuttlefish::start() and cuttlefish::stop(), to define the scope requiring an energy-efficient execution. Whenever Cuttlefish discovers a new TIPI range, it uses DVFS to explore the optimal core frequency, followed by UFS to explore the optimal uncore frequency for this TIPI range. An optimal frequency is the one that has the lowest JPI. Cuttlefish start its execution without any prior information on TIPI ranges and optimal frequencies. The insight is to minimize the application slowdown due to frequency exploration by compacting the exploration range on the fly based on the optimal core and uncore frequencies of other TIPI range discovered since the start of this application.

4.1 Cuttlefish daemon loop

Cuttlefish daemon thread is spawned by the API cuttlefish::start() and is pinned to a fixed core. Algorithm 1 lists the pseudocode implementation of this daemon thread. It sets the core and uncore frequencies to the maximum (Line 2). It runs in a loop where it first calculates the TIPI and JPI for the whole processor (Line 7), followed by execution of the Cuttlefish runtime policy (Line 8–Line 33), and finally goes back to sleep for T\textsubscript{inv} duration (Line 36). The implementation for measuring the TIPI and JPI in Cuttlefish is inspired by the RCRtool [38]. It continues the execution of this loop until cuttlefish::stop() is called inside the user application. From Figure 2(b) and Figure 2(a), we can observe that TIPI and JPI fluctuate heavily at the beginning of the execution timeline. This fluctuation is prominent across all three variants of Heat and SOR and AMG (seven out of ten benchmarks), whereas it’s minuscule in the remaining three benchmarks. This instability is due to cold caches at the start of execution, but it becomes stable after a while. Hence, to avoid recording unstable values of TIPI and JPI, the Cuttlefish daemon loop activates only after a warmup duration of two seconds (Line 3).

4.2 Cuttlefish runtime policy

After every T\textsubscript{inv}, the Cuttlefish policy (Line 8–Line 33) is invoked where it uses DVFS and UFS to determine Optimal Core Frequency (CF\textsubscript{opt}) and Optimal Uncore Frequency (UF\textsubscript{opt}) for a given TIPI range. Cuttlefish maintains a sorted doubly linked list of unique TIPI ranges discovered during an

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Algorithm 1: Cuttlefish daemon thread method

1. \( \text{CF}_{\text{prev}} \leftarrow \text{CF}_{\text{max}} \); \( \text{UF}_{\text{prev}} \leftarrow \text{UF}_{\text{max}} \)
2. \( \text{set_freq}(\text{CF}_{\text{prev}}, \text{UF}_{\text{prev}}) \)
3. \( \text{sleep(\text{warmup duration})} \)
4. \( \text{CF}_{\text{next}} \leftarrow \text{UF}_{\text{next}} \leftarrow -1 \)
5. \( \text{N}_{\text{curr}} \leftarrow \text{N}_{\text{prev}} \leftarrow \text{NULL} \) // TIPI LinkedList nodes

6. \textbf{while} shutdown not initiated from stop API \textbf{do}

7. \hspace{1em} \text{Read TIPI and JPI values from MSR}

8. \hspace{2em} \textbf{if} TIPI NOT found in LinkedList \textbf{then}

9. \hspace{3em} \( \text{N}_{\text{curr}} \leftarrow \text{insert_in_sortedLinkedList}(\text{TIPI}) \)

10. \hspace{4em} \( \text{CF}_{\text{LB}} \leftarrow \text{CF}_{\text{min}}; \text{CF}_{\text{UB}} \leftarrow \text{CF}_{\text{max}} \) // for \( \text{N}_{\text{curr}} \)

11. \hspace{4em} \( \text{UF}_{\text{LB}} \leftarrow \text{UF}_{\text{min}}; \text{UF}_{\text{UB}} \leftarrow \text{UF}_{\text{max}} \) // for \( \text{N}_{\text{curr}} \)

12. \hspace{3em} \text{Reduce CF}_{\text{LB}}/\text{CF}_{\text{RB}} \text{ if LinkedList size} > 1

13. \hspace{3em} \( \text{CF}_{\text{next}} \leftarrow \text{find}(\text{CF}, \text{JPI, CF}_{\text{prev}}, \text{N}_{\text{prev}}, \text{N}_{\text{curr}}) \)

14. \hspace{3em} \( \text{UF}_{\text{next}} \leftarrow \text{UF}_{\text{max}} \)

15. \hspace{1em} \textbf{else}

16. \hspace{2em} \( \text{N}_{\text{curr}} \leftarrow \text{fetch_from_sortedLinkedList}(\text{TIPI}) \)

17. \hspace{3em} \textbf{if} \( \text{N}_{\text{curr}}.\text{CF}_{\text{opt}} \) \& \( \text{N}_{\text{curr}}.\text{UF}_{\text{opt}} \) \( \leftarrow 1 \) \textbf{then}

18. \hspace{4em} \( \text{CF}_{\text{next}} \leftarrow \text{find}(\text{CF}, \text{JPI, CF}_{\text{prev}}, \text{N}_{\text{prev}}, \text{N}_{\text{curr}}) \)

19. \hspace{4em} \( \text{UF}_{\text{next}} \leftarrow \text{UF}_{\text{max}} \)

20. \hspace{3em} \textbf{if} \( \text{N}_{\text{curr}}.\text{CF}_{\text{next}} \leftarrow \text{N}_{\text{curr}}.\text{CF}_{\text{opt}} \) \textbf{then}

21. \hspace{4em} \text{Estimate UF}_{\text{LB}} \& \text{UF}_{\text{RB}} \text{ (Algorithm 3)} // Section 4.4

22. \hspace{4em} \text{Reduce UF}_{\text{LB}}/\text{UF}_{\text{RB}} \text{ if LinkedList size} > 1

23. \hspace{4em} \( \text{UF}_{\text{next}} \leftarrow \text{N}_{\text{curr}}.\text{UF}_{\text{RB}} \)

24. \hspace{1em} \textbf{end}

25. \hspace{1em} \textbf{else if} \( \text{N}_{\text{curr}}.\text{UF}_{\text{opt}} \) \( \leftarrow 1 \) \textbf{then}

26. \hspace{2em} \( \text{CF}_{\text{next}} \leftarrow \text{N}_{\text{curr}}.\text{CF}_{\text{opt}} \)

27. \hspace{2em} \( \text{UF}_{\text{next}} \leftarrow \text{find}(\text{UF}, \text{JPI, UF}_{\text{prev}}, \text{N}_{\text{prev}}, \text{N}_{\text{curr}}) \)

28. \hspace{1em} \textbf{else}

29. \hspace{2em} \( \text{CF}_{\text{next}} \leftarrow \text{N}_{\text{curr}}.\text{CF}_{\text{opt}} \)

30. \hspace{2em} \( \text{UF}_{\text{next}} \leftarrow \text{N}_{\text{curr}}.\text{UF}_{\text{opt}} \)

31. \hspace{1em} \textbf{end}

32. \hspace{1em} \text{set_freq}(\text{CF}_{\text{next}}, \text{UF}_{\text{next}}) \)

33. \hspace{1em} \( \text{N}_{\text{prev}} \leftarrow \text{N}_{\text{curr}} \)

34. \hspace{1em} \( \text{CF}_{\text{prev}} \leftarrow \text{CF}_{\text{next}}; \text{UF}_{\text{prev}} \leftarrow \text{UF}_{\text{next}}; \)

35. \hspace{1em} \text{sleep(\text{T}_{\text{inv}})}

36. \hspace{1em} \textbf{end}
execution. This list is empty at the beginning (Line 8). Each node in this linked list has the following fields: TIPI range, arrays to store JPI for each core and uncore frequencies, latest exploration range for core and uncore frequencies, CF_{opt}, and UF_{opt}. Figure 4(a) shows one such node in this list for a hypothetical processor having seven frequency levels, A–G, for both core and uncore. A and G are the lowest and highest frequencies, respectively, in this processor. To explain the Cuttlefish runtime policy’s working, we use this same hypothetical processor in all our discussions hereafter. The pseudocode implementation of core and uncore frequency exploration is shown in Algorithm 2.

| Algorithm 2: Method find for CF / UF exploration |
|--------------------------------------------------|
| **Input:** type, JPI_{curr}, FQ_{curr}, N_{prev}, N_{curr} |
| **Output:** FQ_{next} |
| 1 ptr = N_{curr}.FQ_table[type] // type is CF/UF |
| 2 if ptr.FQ_{LB} & ptr.FQ_{RB} are adjacent then |
| 3 | Choose FQ_{opt} from FQ_{LB} & FQ_{RB} // Figure 5 |
| 4 | return ptr.FQ_{opt} |
| 5 end |
| // Discard JPI in TIPI transition phase |
| 6 if N_{prev} = N_{curr} then |
| 7 | N_{curr}.JPI_table[type][FQ_{curr}] ← average(JPI_{curr}) |
| 8 end |
| /* JPI_{avg} at any FQ is average of 10 readings. Hence, Line 9 / Line 11 equates to true during TIPI transition due to incomplete JPI_{avg} */ |
| 9 if JPI_{avg} NOT exists for ptr.FQ_{RB} then |
| 10 | return ptr.FQ_{RB} |
| 11 else if JPI_{avg} NOT exists for ptr.FQ_{RB-2} then |
| 12 | return ptr.FQ_{RB-2} |
| 13 end |
| 14 if JPI_{avg} at ptr.FQ_{RB-2} is less than ptr.FQ_{RB} then |
| 15 | ptr.FQ_{RB} ← ptr.FQ_{RB-2} |
| 16 | FQ_{next} = (ptr.FQ_{RB} - ptr.FQ_{LB} > 2) ? ptr.FQ_{RB-2} : ptr.FQ_{LB} |
| 17 else |
| 18 | FQ_{next} ← ptr.FQ_{LB} ← ptr.FQ_{RB-1} |
| 19 end |
| 20 if ptr.FQ_{LB} & ptr.FQ_{RB} are same then |
| 21 | FQ_{next} ← ptr.FQ_{opt} ← ptr.FQ_{RB} |
| 22 end |
| // Section 4.5 |
| 23 return FQ_{LB} or FQ_{RB} of other TIPIs if LinkedList.size >1 |
| 24 return FQ_{next} |

4.3 Frequency exploration in single TIPI-range

Here, we explain the steps followed by the Cuttlefish in exploring the CF_{opt} and UF_{opt} for benchmarks having a single TIPI range (Table 1 lists the total number of distinct TIPI slabs in each benchmark). Cuttlefish starts the exploration first for the CF_{opt} within the default exploration range with the left
bound core and uncore frequencies (CF_{LB} and UF_{LB}, respectively) set to minimum, and the right bound core and uncore frequencies (CF_{RB} and UF_{RB}, respectively) set to maximum (Algorithm 1, Line 10–Line 11). For the hypothetical processor, this exploration is shown in Figure 4, where CF_{LB} = CF_{A} and CF_{RB} = CF_{G}. As execution starts with the frequencies set to CF_{G} and UF_{G}, after the first T_{inv}, the JPI value for CF_{G} is recorded. To ensure stability in the JPI value, Cuttlefish computes the average JPI at CF_{G} across ten T_{inv}. Henceforth, the JPI value reported for any CF and UF in Cuttlefish is an average of ten readings (Algorithm 2, Line 7). Frequency exploration cannot continue until an average of ten readings of JPI is available at a given frequency. Once the JPI is finalized for CF_{G} (Figure 4(a)), Cuttlefish will use DVFS to set the core frequency at CF_{E} without changing the uncore (Algorithm 1, Line 33). Frequencies are always explored at steps of two to minimize the exploration steps. Cuttlefish will then compare the JPIs at CF_{G} and CF_{E} (Figure 4(b)). This comparison is performed at Line 14–Line 16 in Algorithm 2. As CF_{E} has lower JPI than CF_{G}, Cuttlefish will update CF_{RB} = CF_{E} and then set the frequency at CF_{C}. As it turns out that CF_{C} has lower JPI than CF_{E}, now CF_{RB} = CF_{C} (Figure 4(c)), and the frequency would be set to CF_{A}. As even CF_{A} has lower JPI than CF_{C}, CF_{LB} = CF_{RB} = CF_{A} (Algorithm 2, Line 21), thereby making it as CF_{opt} for this TIPI (Figure 4(d)).

Cuttlefish explores both core and uncore frequencies linearly at the steps of two instead of using binary search for reducing the total number of explorations and performance degradation. Except when the optimal frequency lies at the boundary of the exploration range, Cuttlefish cannot use the naive binary search algorithm. When the optimal frequency lies between the exploration range, JPI will increase when moving left/right from the optimal frequency. For example, assume that JPI_{A} < JPI_{G} and E is the optimal frequency for some TIPI (Figure 4). Applying a binary search to find E would require measuring JPIs at mid, mid+1, and mid-1 at each split. This would require more explorations as compared to the linear search (steps of two). For the worst-case scenario (optimal at default minimum), the total number of explorations for CF_{opt} on our Intel Haswell processor
using linear search would be six (total_frequencies/2) compared to eight by using the modified binary search. Also, as the JPI at each frequency is an average of ten values, exploring mid, mid+1, and mid-1 frequencies in binary search exploration would cause more performance degradation than linear search (highest to lowest).

After exploring CF\textsubscript{opt} = CF\textsubscript{A}, Cuttlefish will start the exploration for UF\textsubscript{opt} by fixing the core frequency to CF\textsubscript{A} (Algorithm 1, Line 20). However, for UF\textsubscript{opt}, Cuttlefish would not explore the default exploration range of UF\textsubscript{LB} = UF\textsubscript{A} to UF\textsubscript{RB} = UF\textsubscript{G}. Instead, it uses Algorithm 3 to estimate the uncore exploration range (Algorithm 1, Line 21). Algorithm 3 is based on our observation in Section 3.2 that a high core frequency as optimal implies a low uncore frequency as optimal, and vice-versa. Hence, CF\textsubscript{opt} = CF\textsubscript{max} implies that UF\textsubscript{opt} = UF\textsubscript{min}, and CF\textsubscript{opt} = CF\textsubscript{min} implies UF\textsubscript{opt} = UF\textsubscript{max}. Now, for estimating the optimal uncore (UF\textsubscript{opt_est}) based on the CF\textsubscript{opt}, we use the curve-fitting technique, where we map the coordinates (CF\textsubscript{max}, UF\textsubscript{min}) and (CF\textsubscript{min}, UF\textsubscript{max}) on a straight line. It is shown in Lines 2-3 of Algorithm 3. We also saw the latest Intel processor’s trend that the number of uncore frequencies and core frequencies is roughly similar. Hence, to prepare a short exploration range for UF, we calculate the ratio of the number of uncore frequencies and core frequencies. To get a modest exploration space, we are multiplying the ratio by a constant of 4. This ratio calculation is shown in Line 1 of Algorithm 3. Line 4–Line 11 of Algorithm 3 shows the UF\textsubscript{LB} and UF\textsubscript{RB} calculation that uses the range and ratio described above. By using this Algorithm, Cuttlefish uses the exploration range of UF\textsubscript{LB} = UF\textsubscript{C} and UF\textsubscript{RB} = UF\textsubscript{G}, and continues the UF\textsubscript{opt} exploration similar to the CF\textsubscript{opt} exploration (Figure 4(e) and Figure 4(f)).

Algorithm 3: Algorithm to find UF exploration range

\textbf{Input:} CF\textsubscript{opt}  \\
\textbf{Output:} UF\textsubscript{LB}, UF\textsubscript{RB}

1. Range ← 4 * (UF\textsubscript{max} - UF\textsubscript{min} + 1)/(CF\textsubscript{max} - CF\textsubscript{min} + 1)
2. \(\alpha\) ← (UF\textsubscript{max} - UF\textsubscript{min})/(CF\textsubscript{max} - CF\textsubscript{min})
3. UF\textsubscript{opt_est} ← UF\textsubscript{max} - (\(\alpha\) * (CF\textsubscript{opt} - CF\textsubscript{min}))
4. UF\textsubscript{LB} ← \text{max}(UF\textsubscript{min}, UF\textsubscript{opt_est} - Range/2)
5. UF\textsubscript{RB} ← \text{min}(UF\textsubscript{max}, UF\textsubscript{opt_est} + Range/2)
6. if \(UF\textsubscript{max} - UF\textsubscript{opt_est} \leq \text{Range}/2\) then
7.  \hspace{1cm} UF\textsubscript{LB} ← UF\textsubscript{LB} - (UF\textsubscript{opt_est} + Range/2 - UF\textsubscript{max})
8. end
9. if \(UF\textsubscript{opt_est} - UF\textsubscript{min} \leq \text{Range}/2\) then
10.  \hspace{1cm} UF\textsubscript{RB} ← UF\textsubscript{RB} + (UF\textsubscript{min} - (UF\textsubscript{opt_est} - Range/2))
11. end

Figure 4 depicted the situation where reducing the frequency was reducing the JPI. However, there will be scenarios where reducing the frequency increases the JPI. These situations are depicted in Figure 5 when low bound and high bound frequencies are adjacents (Algorithm 2, Line 2–Line 5). In Figure 5(a), JPI at CF\textsubscript{E} was higher than that at CF\textsubscript{G}. In this case, CF\textsubscript{LB} = CF\textsubscript{F}. However, as the CF\textsubscript{LB} and CF\textsubscript{RB} (CF\textsubscript{G}) are consecutive frequencies, CF\textsubscript{opt} will be set to CF\textsubscript{G} to minimize the loss in performance as high CF indicates a compute-bound MAP. Figure 5(b) depicts a situation where JPI at CF\textsubscript{E} was higher than that at CF\textsubscript{C}. In this case, CF\textsubscript{LB} = CF\textsubscript{B}. Again, left bound CF\textsubscript{LB} and CF\textsubscript{RB} (CF\textsubscript{C}) are consecutive frequencies, but this time CF\textsubscript{opt} will be set to CF\textsubscript{B} to maximize the energy efficiency as low CF indicates a memory-bound MAP. These two scenarios depicted for CF can also occur for UF.

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4.4 Frequency exploration for subsequent TIPIs

An application could have a variety of MAP, e.g., in AMG, we found 60 distinct MAPs (Table 1). Using the default CF exploration range $CF_{LB} = CF_A$ and $CF_{RB} = CF_G$ for every newly discovered TIPIs can easily degrade the application performance, especially on a processor supporting a wide range of frequencies. Hence, Cuttlefish uses the default $CF_{LB}$ and $CF_{RB}$ only for the first TIPI (Algorithm 1, Line 10–Line 11). For subsequent TIPIs, it sets $CF_{LB}$ and $CF_{RB}$ based on the $CF_{opt}$ and the latest values of $CF_{LB}$ and $CF_{RB}$ in previously discovered TIPI ranges. Here, the insight is to use a sorted doubly linked list of TIPI ranges, where moving from left to right in the linked list signifies a shift from compute-bound MAP to memory-bound MAP. Hence, when a new TIPI node is inserted in
the linked list, Cuttlefish can look up the $\text{CF}_{\text{opt}}$, $\text{CF}_{\text{LB}}$ and $\text{CF}_{\text{RB}}$ of its adjacent nodes (left and right) to dynamically decide the $\text{CF}_{\text{LB}}$ and $\text{CF}_{\text{RB}}$ for this new TIPI node. Compared to $\text{CF}$, the exploration range of $\text{UF}$ is already smaller (Algorithm 3). Still, Cuttlefish attempts to reduce this exploration range even further for subsequent TIPIs by following the same insight mentioned above for $\text{CF}$. This optimization is shown in Figure 6 for $\text{CF}$ exploration (Algorithm 1, Line 12) and in Figure 7 for $\text{UF}$ exploration (Algorithm 1, Line 22).

Figure 6(a) shows an execution phase $N$ (time elapsed since Cuttlefish started is $N \times T_{\text{inv}}$), at which MAP was pointing to TIPI-3, but a new TIPI range, TIPI-1, was discovered by the Cuttlefish. Comparing TIPI-1 with other TIPIs in the linked list, it is found that TIPI-1 should be added in the front. The position of the TIPI-1 signifies that it is compute-bound relative to the TIPI-3, i.e., $\text{CF}_{\text{opt}}$ for TIPI-1 will be the same or greater than the $\text{CF}_{\text{opt}}$ for TIPI-3. Hence, $\text{CF}_{\text{LB}} = \text{CF}_{B}$ and $\text{CF}_{\text{RB}} = \text{CF}_{G}$ for TIPI-1. As there was a TIPI transition in the last $T_{\text{inv}}$ phase, JPI calculated for $\text{CF}_{B}$ is not recorded in the $\text{CF}$ table for TIPI-1 (Algorithm 2, Line 6–Line 8). It will be recorded after the next $T_{\text{inv}}$ phase. After a few execution duration with the MAP still pointing to TIPI-1, another new TIPI, TIPI-2, was discovered by the Cuttlefish. This is shown in Figure 6(b). At this time, Cuttlefish calculated the JPI for $\text{CF}_{C}$ to compare it with the JPI at $\text{CF}_{E}$ in TIPI-1. However, it won’t be able to do so because the new TIPI-2 was discovered in the last $T_{\text{inv}}$. By comparing TIPI-2 with other TIPIs, it found that the TIPI-2 node should be inserted between the TIPI-1 and TIPI-3 nodes in the linked list. This signifies that TIPI-2 is memory-bound relative to the TIPI-1 but compute-bound relative to the TIPI-3. Hence, going by the same algorithm as in TIPI-1, TIPI-2’s $\text{CF}_{\text{LB}}$ and $\text{CF}_{\text{RB}}$ should be the $\text{CF}_{\text{opt}}$ for TIPI-3 and TIPI-1, respectively. However, as the $\text{CF}_{\text{opt}}$ for TIPI-1 is still not found, TIPI-2’s $\text{CF}_{\text{RB}}$ will be set to $\text{CF}_{\text{RB}}$ of TIPI-1 ($\text{CF}_{E}$). Due to the TIPI transition in the last phase, the JPI ($\text{CF}_{C}$) of the last $T_{\text{inv}}$ will not be recorded in TIPI-2.

Figure 7 demonstrates the same optimization discussed above, but only for uncore exploration. Figure 7(a) shows an execution phase when Cuttlefish has found the $\text{CF}_{\text{opt}}$ for TIPI-1, and now it has to start the exploration of $\text{UF}_{\text{opt}}$ for TIPI-1. By using Algorithm 3, $\text{UF}_{\text{LB}} = \text{UF}_{A}$ and $\text{UF}_{\text{RB}} = \text{UF}_{E}$ for TIPI-1. As TIPI-1 is compute-bound relative to the TIPI-3, its $\text{UF}_{\text{opt}}$ will be the same or lower.
than the \( UF_{\text{opt}} \) (\( UF_C \)) for TIPI-3. Hence, \( UF_{RB} = UF_C \) for TIPI-1. This is precisely opposite to what was done in the case of CF. Figure 7(b) shows an execution phase when Cuttlefish has found the CF\(_{\text{opt}}\) for TIPI-2, and now it has to start exploring \( UF_{\text{opt}} \) for TIPI-2. It sets the \( UF_{\text{opt}} \) of TIPI-3 as \( UF_{RB} \) for TIPI-2 and \( UF_{\text{opt}} \) of TIPI-1 as \( UF_{LB} \) of TIPI-2. TIPI-2 is memory-bound relative to TIPI-1. Hence its \( UF_{\text{opt}} \) will be the same or higher than the \( UF_{\text{opt}} \) of TIPI-1.

### 4.5 Revalidating frequency exploration range

Previous sections described the optimizations carried out in Cuttlefish to reduce the frequency exploration range when the exploration is about to start. This section describes the third and final optimization in Cuttlefish to shrink the exploration range even further after the exploration has begun (Algorithm 2, Line 23).

![Diagram](image)

**Fig. 8.** Revalidation of CF exploration range

Figure 8(a) shows a phase change from left to right after some \( T_{\text{inv}} \). There are two TIPIs, TIPI-1 and TIPI-2, in the linked list, where TIPI-1 is compute-bound relative to TIPI-2. Before the phase change, MAP was set to TIPI-2 with its CF\(_{LB} = CF_B \) and \( CF_{RB} = CF_E \). JPI for \( CF_E \) has been evaluated for TIPI-2. Now Cuttlefish has to calculate the JPI for \( CF_C \) for TIPI-2. TIPI-1’s \( CF_{LB} = CF_B \) and \( CF_{RB} \)
=CF_G. After some T_{inv}, Cuttlefish evaluates the JPI for CF_C and found it more than the JPI for CF_E. Hence, for TIPI-2 (Figure 8(a)), it would update the CF_{LB} = CF_D and set CF_{opt} = CF_E as CF_{LB} and CF_{RB} are consecutive frequencies (Section 4.3). However, as TIPI-1 is compute-bound relative to TIPI-2, Cuttlefish will also update the CF_{LB} = CF_E (CF_{opt} for TIPI-2). In Figure 8(b), after the phase change, Cuttlefish calculates that JPI at CF_E is better than that at CF_G for TIPI-3. Hence, it updates the CF_{RB} = CF_E for TIPI-3. However, as TIPI-4 is memory-bound relative to the TIPI-3, Cuttlefish will also update the CF_{RB} of TIPI-4 to that of TIPI-3.

Figure 9 demonstrates the same optimization discussed above, but only for revalidating the uncore exploration range. In Figure 9(a), before phase change from left to right, MAP was set to TIPI-5 with the JPI available for UF_{RB} = UF_G. Uncore was then set to UF_E, and after some T_{inv}, JPI at UF_E was found to be less than that at UF_G for TIPI-5. This changed the UF_{RB} from UF_G to UF_E at TIPI-5. However, as TIPI-4 is compute-bound relative to the TIPI-5, its UF_{RB} will also shift from UF_G to UF_E.

In Figure 9(b), before phase change from left to right, MAP was set to TIPI-4 with the JPI available for UF_{RB} = UF_E. Uncore was then set to UF_C, and after some T_{inv}, JPI at UF_C was found to be more than
Fig. 10. Experimental evaluation using OpenMP

that at $UF_E$ for TIPI-4. This changes the $UF_{LB}$ from $UF_C$ to $UF_D$ at TIPI-4. Now, as the $UF_{LB}$ and $UF_{RB}$ at TIPI-4 are consecutive frequencies, $UF_{opt}$ for TIPI-4 will be set to $UF_E$. As TIPI-5 is memory-bound relative to the TIPI-4, its $UF_{LB}$ will also shift from $UF_C$ to $UF_E$ (TIPI-4’s $UF_{opt}$). However, now as both $UF_{LB}$ and $UF_{RB}$ in TIPI-5 points to $UF_E$, its $UF_{opt}$ will also be set to $UF_E$.

4.6 Cuttlefish in distributed computing

Cuttlefish is currently suitable for profiling a single multicore parallel program. Hence, one can also use it in MPI+X style distributed computing programs, where a single process is executed at each node for inter-node communications (MPI, UPC++, etc.), and a multithreaded library (e.g., OpenMP) is used for parallelizing intra-node computations. However, Cuttlefish cannot regulate the processor frequencies to mitigate the workload imbalance between the process [4]. Thereby, its scope is limited to the node level parallel regions (e.g., OpenMP) in regular MPI+X parallel programs that do not exhibit any load-imbalance due to overlapping computation and communication. We aim to extend Cuttlefish for achieving energy efficiency in MPI+X style hybrid parallel programs as future work.

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5 EXPERIMENTAL EVALUATION

We provide build-time flags for the three different policies, Cuttlefish, Cuttlefish-Core, and Cuttlefish-Uncore, in the Cuttlefish library. Section 4 described the design and implementation of Cuttlefish that dynamically changes both the core and uncore frequencies. Cuttlefish-Core and Cuttlefish-Uncore are the subsets of the Cuttlefish implementation. Cuttlefish-Core only adapts the core frequencies by fixing the uncore frequency at its maximum (3.0GHz). Cuttlefish-Uncore only adjusts the uncore frequencies by setting the cores frequency at its maximum (2.3GHz). For the first TIPI-range, both Cuttlefish-Core and Cuttlefish-Uncore start the frequency exploration described in Section 4.3 in their respective default exploration ranges (1.2GHz-2.3GHz for core and 1.2GHz-3.0GHz for uncore). For subsequent TIPI ranges, they use all the runtime optimizations described in Section 4.4 and Section 4.5 but restrict these optimizations to core-only in Cuttlefish-Core and uncore-only in Cuttlefish-Uncore.

We begin our evaluation of Cuttlefish policies by measuring energy savings and slowdown for both OpenMP and HClib benchmarks. We then compare the $CF_{opt}$ and $UF_{opt}$ calculated by the Cuttlefish to Default for all frequent TIPI ranges.

5.1 Evaluation of OpenMP benchmarks

Figures 10(a), 10(b), and 10(c) compare the energy savings, execution time, and EDP, respectively, of the OpenMP benchmarks while using Cuttlefish’s policies to that of the Default. Recall from Section 2, Default was executed by setting the performance power governor that runs each core at the highest frequency (2.3GHz). During the Default execution, uncore frequency is controlled by the processor based on the memory access pattern. Geomean energy-savings with Cuttlefish, Cuttlefish-Core, and Cuttlefish-Uncore are 19.6%, 3.1%, and 9.9%, respectively. Geomean loss in performance with Cuttlefish, Cuttlefish-Core, and Cuttlefish-Uncore are 3.6%, 2.5%, and 3%, respectively. Compared to the Default, Cuttlefish-Core required more energy in UTS, SOR-irt, SOR-rt, and SOR-ws. As these benchmarks are purely compute-bound (see TIPI-range in Table 1), Cuttlefish-Core would fix the $CF_{opt}$ for these benchmarks at the highest frequency (2.3GHz). However, unlike Cuttlefish-Core, the Default optimizes the uncore frequency, thereby requiring less energy than Cuttlefish-Core. Geomean EDP savings by Cuttlefish, Cuttlefish-Core, and Cuttlefish-Uncore are 16.5%, 0.7%, and 7.2%, respectively, over the Default.

For memory-bound benchmarks (Heat variants, MiniFE, HPCCG, and AMG), energy-savings from Cuttlefish-Core and Cuttlefish-Uncore are almost similar (the difference is less than 5%). Although there is some degradation in time, the max is 6.3% (Heat-ws). This demonstrates that using Cuttlefish even in core-only or uncore-only mode is also quite effective for memory-bound benchmarks. As Cuttlefish adapts both core and uncore frequencies, it has the potential to save energy in both compute and memory-bound benchmarks. Energy savings are higher in the memory-bound benchmarks because Cuttlefish can adapt both the uncore and core frequencies. However, as it has to explore both these cases, the performance degradation is slightly higher (max 8.1% in MiniFE) than the compute-bound benchmarks (max 1.6% in UTS).

5.2 Evaluation of HClib benchmarks

To support our hypothesis that Cuttlefish is a programming model oblivious, we now present the evaluation of Cuttlefish policies using HClib implementations of SOR and Heat variants. We omit MiniFE, HPCCG, and AMG due to porting challenges. We also discarded UTS as this benchmark has an inbuilt work-stealing implementation, and modifying it to use HClib would alter its algorithm. HClib supports async-finish task parallelism and internally uses a work-stealing runtime for dynamic load-balancing these asynchronous tasks. The results of this experiment are shown in
Figure 11. Figure 11(a), Figure 11(b), and Figure 11(c) compare the energy savings, time degradation, and EDP, respectively, for Cuttlefish policies to that of the Default. Comparing these results with Figure 10 shows that Cuttlefish delivers similar results in HClib and OpenMP benchmarks.

5.3 Frequency settings using Cuttlefish

Table 2 shows the percentage of distinct TIPI ranges (see Table 1) for which Cuttlefish was able to find the CF_{opt} and UF_{opt} in OpenMP benchmarks. This table also lists the CF_{opt} and UF_{opt} set by the Cuttlefish for frequently found TIPI ranges and then compare them with the Default settings. AMG was having the highest number of distinct TIPI ranges (total 60), due to which it experiences a wide variation in MAP during the execution timeline (Figure 2(b)). Cuttlefish discovered CF_{opt} and UF_{opt} in 68% and 3% of the distinct TIPIs, respectively, even for such an unstable execution. We found that the major exploration was carried out only for the frequently found TIPI ranges (total two). Still, optimal frequencies for the rest were mostly set using the runtime optimizations described in Section 4.4 and Section 4.5. As 58 of the 60 distinct TIPI ranges appear in less than 10% of the total T_{inv} durations, Cuttlefish doesn’t get too many opportunities to explore UF_{opt} in AMG for these infrequent TIPI ranges (CF_{opt} is explored before UF_{opt}).
For the frequently found TIPI ranges in each benchmark, Cuttlefish accurately set both the CF\textsubscript{opt} and UF\textsubscript{opt}. These frequencies match the trend observed during motivational analysis in Section 3.2. Heat-rt has only two distinct TIPI ranges. Although TIPI 0.060-0.064 appears during 15% of T\textsubscript{inv} durations in Heat-rt, their occurrences are widespread across the execution timeline. Hence, in Heat-rt, Cuttlefish could not set CF\textsubscript{opt} and UF\textsubscript{opt} for the TIPI range 0.060-0.064. Due to the performance power governor in Default, the CF was set to 2.3GHz (CF\textsubscript{max}). The processor’s uncore settings in Default were 2.2GHz and 3.0GHz (UF\textsubscript{max}) for compute-bound and memory-bound benchmarks, respectively.

### 5.4 Sensitivity to T\textsubscript{inv}

This section discusses the impact of T\textsubscript{inv} on the overall energy savings and slowdown from using Cuttlefish. Table 3 compares the geomean energy savings and slowdown of OpenMP benchmarks relative to Default by using Cuttlefish at different values of T\textsubscript{inv}. RAPL MSRs are updated every 1 ms on Intel Haswell [24]. Hence, we chose T\textsubscript{inv} as 10×, 20×, 40×, and 60× of this processor default. We can observe there is a marginal decrease in energy savings and slowdown with increasing

#### Table 2. CF\textsubscript{opt} and UF\textsubscript{opt} set by Cuttlefish in OpenMP benchmarks and its comparison with the Default settings

| Benchmark | TIPI ranges (%) having CF\textsubscript{opt} and UF\textsubscript{opt} | Frequent TIPI Ranges | Cuttlefish | Default |
|-----------|-------------------------------------------------|----------------------|------------|---------|
|           | CF\textsubscript{opt} | UF\textsubscript{opt} | CF\textsubscript{opt} | UF\textsubscript{opt} | CF | UF\textsubscript{opt} |
| UTS       | 100% | 100% | 0.000-0.004 (100%) | 2.3 (±0%) | 1.3 (±9%) | 2.3 | 2.2 |
| SOR-irt   | 100% | 100% | 0.024-0.028 (100%) | 2.3 (±0%) | 1.2 (±0%) | 2.3 | 2.2 |
| SOR-rt    | 100% | 100% | 0.024-0.028 (100%) | 2.3 (±0%) | 1.2 (±5%) | 2.3 | 2.2 |
| SOR-ws    | 100% | 100% | 0.024-0.028 (93%) | 2.3 (±0%) | 1.2 (±0%) | 2.3 | 2.2 |
| Heat-irt  | 50%  | 25%  | 0.064-0.068 (88%) | 1.2 (±0%) | 2.2 (±0%) | 2.3 | 3.0 |
| Heat-rt   | 33%  | 33%  | 0.060-0.064 (15%) | -          | -          | 2.3 | 3.0 |
| Heat-ws   | 18%  | 9%   | 0.050-0.060 (88%) | 1.3 (±9%) | 2.2 (±1%) | 2.3 | 3.0 |
| MiniFE    | 44%  | 6%   | 0.112-0.116 (76%) | 1.3 (±9%) | 2.2 (±1%) | 2.3 | 3.0 |
| HPCCG     | 35%  | 6%   | 0.120-0.124 (76%) | 1.3 (±9%) | 2.2 (±1%) | 2.3 | 3.0 |
| AMG       | 68%  | 3%   | 0.144-0.148 (56%) | 1.3 (±11%)| 2.2 (±1%) | 2.3 | 3.0 |

#### Table 3. Geomean energy savings and slowdown in OpenMP benchmarks using different values of T\textsubscript{inv} in Cuttlefish

| T\textsubscript{inv} | Energy Savings | Slowdown |
|-----------------------|----------------|---------|
| 10ms                  | 19.5%          | 4.1%    |
| 20ms                  | 19.4%          | 3.6%    |
| 40ms                  | 18.8%          | 2.9%    |
| 60ms                  | 17.8%          | 2.9%    |

For the frequently found TIPI ranges in each benchmark, Cuttlefish accurately set both the CF\textsubscript{opt} and UF\textsubscript{opt}. These frequencies match the trend observed during motivational analysis in Section 3.2. Heat-rt has only two distinct TIPI ranges. Although TIPI 0.060-0.064 appears during 15% of T\textsubscript{inv} durations in Heat-rt, their occurrences are widespread across the execution timeline. Hence, in Heat-rt, Cuttlefish could not set CF\textsubscript{opt} and UF\textsubscript{opt} for the TIPI range 0.060-0.064. Due to the performance power governor in Default, the CF was set to 2.3GHz (CF\textsubscript{max}). The processor’s uncore settings in Default were 2.2GHz and 3.0GHz (UF\textsubscript{max}) for compute-bound and memory-bound benchmarks, respectively.

5.4 **Sensitivity to T\textsubscript{inv}**

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Recall from Section 5.1, Cuttlefish saved more energy in memory-bound benchmarks (22%–29%) than compute-bound (8%–10.1%), but with some performance degradation (3.6%–8.1%). This is because optimal frequencies were lower for both core (1.2GHz/1.3GHz) and uncore (2.2GHz) in memory-bound benchmarks (Table 2). As Cuttlefish performs frequency exploration linearly, starting from the highest to lowest frequencies, higher $T_{inv}$ increases the exploration time, thereby allowing benchmarks to run longer at higher frequencies, causing a slight reduction in energy savings and slowdown. We chose $T_{inv} = 20ms$ as the default configuration of Cuttlefish, as it achieved similar energy savings as with $T_{inv} = 10ms$, but with lesser slowdown.

5.5 Summary
The encouraging results for Cuttlefish demonstrate its efficacy for achieving energy efficiency using a combination of DVFS and UFS on modern multicore processors in a wide range of applications with minimal impact on execution time. Cuttlefish, therefore, promises a one-stop solution as it uses both these dynamically available fine-grain power controls on Intel processors to regulate power. Its two variants, Cuttlefish-Core and Cuttlefish-Uncore, provide alternatives to using both DVFS and UFS together. Overall, Cuttlefish-Uncore achieved better EDP than Cuttlefish-Core. While Cuttlefish-Uncore is suitable for both compute and memory-bound applications, Cuttlefish-Core is not ideal for compute-bound applications as it sets the uncore to the maximum frequency that is otherwise adaptable in the default settings. However, on memory-bound applications, Cuttlefish-Core was able to deliver EDP close to that of Cuttlefish-Uncore.

6 RELATED WORK
Most energy-efficient HPC research in software has focused on making efficient use of microarchitectural power control support available. DVFS is supported by both AMD and Intel processors. It has been the primary choice to control processor frequency in several studies [4, 5, 16, 17, 23, 27, 29, 39, 41, 47]. In the past, processors provided only chip-level DVFS where a frequency change affected all the cores. Most modern processors today support core-specific implementations of DVFS, allowing each core to operate at different frequencies. Intel has provided core-specific support for DVFS from its Haswell generation processors. DDCM has also been used to control processor frequency at a core level in several studies [6, 46, 50].

The target programming model of prior work has dictated much of their design and implementation decisions. The approaches that target the Message Passing Interface (MPI) applications mainly involve mitigation of workload imbalance between the process (slack) [4, 16, 29, 41]. Other MPI-centric solutions address cases where the processor cores wait on the memory or network [5, 22, 26, 43, 48, 49]. Concurrency throttling has been widely used by adapting the thread count in OpenMP programs that are memory-constrained to reduce power consumption [12, 13, 31, 37]. Methods [52] that involve assigning optimal frequencies to OpenMP loops based on their memory access patterns have been proposed. Static analysis of loop-based parallel programs has been used to compute each loop chunk’s workload and then tune the chip frequency dynamically by calculating the remaining workload [42]. Iterative parallel programs provide an opportunity to dynamically tune the frequencies of the cores according to the workload information of the tasks collected with the online profiling of the first few iterations [9]. The impact of power capping on compiler transformations has been studied by utilizing the memory access density information of OpenMP loops [51]. Fine-tuning the core frequencies based on online profiling of thief-victim relationships and the size of deques in a work-stealing runtime is another approach for programming model-specific solution [40]. There have been attempts to standardize the interfaces controlling power at different levels of the HPC system hierarchy. GEOPM [14] is one such implementation that leverages feedback from the application to identify which nodes are on the critical path and then
adjusts processor power cap settings to accelerate the critical path and improve the application’s
time-to-solution. The current effort may easily fit as a part of the third-party software components
that GEOPM and such standardized interfaces support.

UFS is a recent research topic for achieving energy efficiency, although it has been available
to the user since the Intel Haswell processor generation [21]. The high efficacy of UFS has been
demonstrated in terms of its energy-saving potential [45]. UFS has been used to dynamically adapt
the uncore frequency based on the DRAM power usage [18]. A machine learning-based UFS model
has been proposed to gather performance metrics from offline executions and predict the optimal
uncore frequency [3]. The work described in [44] aims to achieve energy efficiency by using both
DVFS and DRAM scaling. However, unlike Cuttlefish, this implementation needs prior data to
learn some machine-dependent parameters using regression analysis. These parameters are used at
runtime to calculate the optimal core and uncore frequency.

7 CONCLUSION

In this paper, a programming model oblivious C/C++ library is proposed for achieving energy
efficiency that is not limited by language constraints and semantics. The model can detect the
changes in the memory access patterns even for the same application across multiple language
implementations to assign optimal frequencies. Using both DVFS and UFS allows additional energy
savings than solutions that utilize a single power control. The effectiveness of the current approach
is demonstrated for irregular-tasking as well as work-sharing pragmas. The use of both micro-
kernels and real-world HPC mini-applications for evaluation helps better understand the library’s
efficacy for production use.

In the future, we would like to extend this framework to support hybrid MPI+X applications.
With the emergence of scientific workflows in HPC systems, we want to explore the possibility of
using Cuttlefish to control the power of co-running components of a workflow on a node. Graphics
processing units (GPUs) are ever more prevalent in HPC today. The energy-efficiency potential in
the context of GPU-offload support offered by many high-level languages is another area worth
exploring.

ACKNOWLEDGMENTS

The authors are grateful to the anonymous reviewers for their suggestions on improving the
presentation of the paper. Results presented in this paper were obtained using the Chameleon
testbed supported by the National Science Foundation. This research used resources of the National
Energy Research Scientific Computing Center, a DOE Office of Science User Facility supported by
the Office of Science of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

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