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Implementation of Scheduling Algorithms in an OpenMP Runtime Library

Master Thesis

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Abstract

Loops are the biggest source of parallelism in parallel programs. The scheduling task, in which the iterations of a loop are assigned to available processors, plays an important role in how efficiently the underlying system is used. OpenMP, the de-facto standard for parallelism, lists three loop scheduling techniques, static, dynamic and guided. Implementations of that standard must support at least these three to meet the OpenMP specification. Existing OpenMP runtime libraries, such as GCC's libgomp or LLVM's libomp, provide ready-to-use scheduling techniques for programmers, however, intensive research from the past has shown multiple and more advanced loop scheduling techniques that are not implemented in these libraries. As recent works have tested the advanced techniques in existing runtimes, it has been proven that depending on the system, application and loop characteristics, one strategy is superior to the others. Libraries must, therefore, implement more techniques in order to provide the best performance for a broad range of distinctive loops. The LLVM OpenMP runtime library, which has a big impact on the industry, still misses many of the techniques to be implemented and tested. This thesis implements numerous dynamic loop scheduling algorithms into the LLVM OpenMP runtime library. Different benchmarks from suites including NAS 3.4, CORAL, Rodinia and SPEC OMP 2012 are chosen to evaluate and compare the new techniques to the available solutions. The results justify that each newly implemented technique can outperform every other in particular software and hardware configurations. Performance improvements of up to 6 % are measured in comparison to the fastest available OpenMP strategy and up to 7 % in unequal threads-per-core bindings. The experiments indicate that increasing numbers of cores per node and heterogeneous systems benefit even more from the implementation and require advanced software for the most efficient usage. In future OpenMP versions, an extension to the techniques of the standard would be a desirable update allowing the user to better exploit parallelism.

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Abbreviations

ADLS	Adaptive DLS
AF	Adaptive Factoring
AWF	Adaptive Weighted Factoring
BOLD	The Bold Strategy
c.o.v.	coefficient of variation
DLS	Dynamic Loop Scheduling
FAC	Factoring
FRAC	Fractiling
FSC	Fixed Size Chunking
GCC	GNU Compiler Collection
GSS	Guided Self-Scheduling
KNL	Knights Landing
libgomp	GNU Offloading and Multi Processing Runtime Library
libomp	LLVM OpenMP runtime library
NADLS	Nonadaptive DLS
OpenMP	Open Multi-Processing
OpenMP API	OpenMP Application Programming Interface
PUs	Processing Units
SC	Static Chunking
SRR	Smart Round-Robin
SS	Self-Scheduling
TAP	Taper
TSS	Trapezoid Self-Scheduling
WF	Weighted Factoring

1 Introduction

Parallelization is more and more coming into the limelight with computer systems that have an increasing number of *Processing Units* (PUs) . The software, however, must evolve as well to efficiently use current computer systems and push them to their limits. Scientific applications, for instance, which typically have a big demand for execution power, would benefit greatly of such an efficient system utilization. These applications are often composed by large loops which usually are a good source of parallelism. Therewith, many research efforts have been done to enhance and exploit the possible parallelizations for such applications. How the workload of a loop, i.e., the iterations, are scheduled, has a big impact on the resulting performance of parallelizing scientific applications. For exactly this task, there exist multiple so called loop scheduling techniques. The reason for their existence lies in the characteristics of applications and their loops. Loop iteration execution times can vary and thus have a negative impact on the system's load balance. Assigning equal amount of iterations to each PU could end up in one PU taking much more time for executing its portion because of these variations, while the rest is waiting. Such loops are also called irregular loops. The techniques counteract this issue. They differ in assigning iterations either statically or dynamically. Static in a way, where a loop is split into fixed-size portions for each PU prior to the execution. Static techniques are well suited for regular loops, where the iterations' execution times are similar. In contrast, *Dynamic Loop Scheduling* (DLS) techniques balance the load during execution and are the prominent choice when it comes to irregular loops with varying iteration execution times. Depending on which DLS method is used, the amount of iterations assigned to a PU at a time varies. Among all the different techniques, one can characterize them in two dimensions. One being the degree of load balancing provided and the other how much overhead the scheduling algorithm itself produces. The ideal case would be maximum load balance with minimum scheduling overhead. Sadly, this is not possible since scheduling requires chunk size calculations of iterations, bookkeeping, communication and more. The extremes are formed by the two techniques static scheduling and *Self-Scheduling* (SS) as depicted in figure 1.1. Unlike static, SS dynamically schedules a single iteration at a time during the execution of a loop, promising best load balance. Details can be found in Chapter 2, Section 2.2. Nevertheless, depending on the loop, one technique should be chosen that fits best. Fortunately, there is a standard-

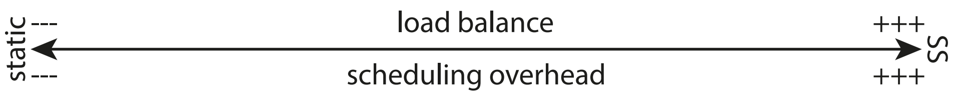


Figure 1.1: The interaction between load balancing and scheduling overhead. Maximizing load balance typically induces scheduling overhead. Static scheduling and SS mark the extremes of all existing techniques.

ized way in how to parallelize code. The *Open Multi-Processing* (OpenMP) specification [1] defines the *OpenMP Application Programming Interface* (OpenMP API) for parallelism in C, C++ and Fortran programs. Many popular compilers already support this specification and provide parallelization for developers [2]. OpenMP does not only require a compiler that supports the specification, but also a runtime library which provides an interface to the compiler. The scheduling task, for instance, is handled by that library. There exist multiple runtime implementations, such as the *LLVM OpenMP runtime library* (libomp) for LLVM's Clang compiler [3] or *GNU Offloading and Multi Processing Runtime Library* (libgomp) [4] for the *GNU Compiler Collection* (GCC) [5]. Runtime library routines are used to examine and modify execution parameters during runtime, e.g., getting the available number of PUs or the number of threads. The user can benefit from these routine functions in source code which then later are handled by the runtime library. As an example, the LLVM Clang compiler has its libomp [3], which handles calls from the running application, as well as the user-level runtime routines. To better understand how OpenMP works, figure 1.2 shows its solution stack [6]. The runtime library is hereby linked to the application whenever it is executed.

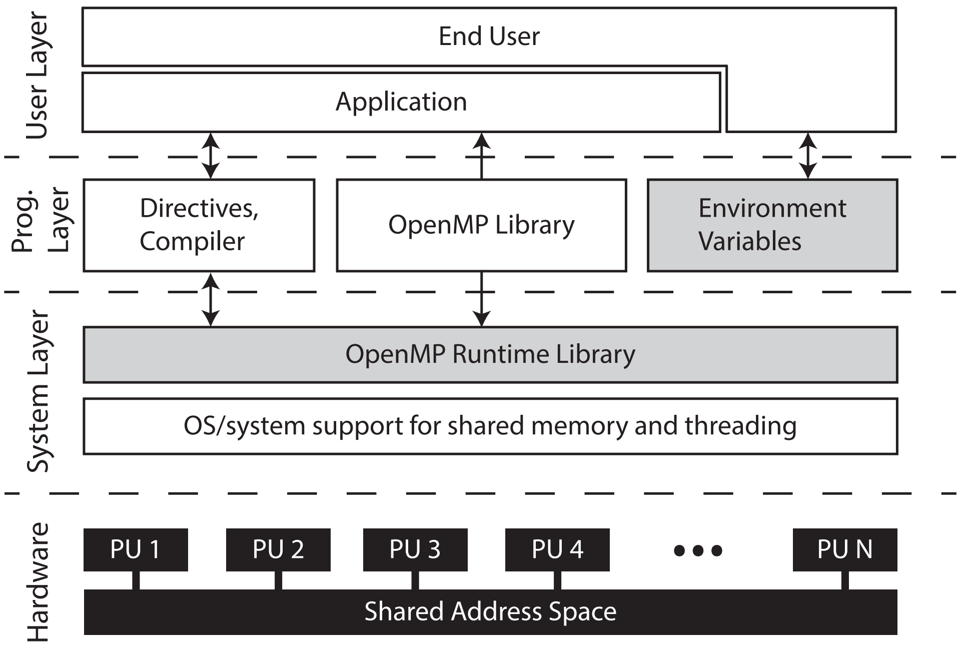


Figure 1.2: The solution stack of OpenMP. Our focus lies on the shaded boxes, namely, the runtime library and environment variables.

The problem with OpenMP arises, when taking a closer look at its scheduling specification.

OpenMP specifies three loop scheduling techniques, all of which are implemented in the above mentioned libraries. These three are `static`, `dynamic`, which is very similar to SS, and `guided`. The latter tries to find a balance in scheduling overhead and load balancing between `static` and `dynamic` by assigning decreasing size chunks of iterations, which corresponds to *Guided Self-Scheduling* (GSS) . However, there are many more methods that come up with better performance on different machines or types of loops. Being restricted to only three algorithms could lead to severe inefficiency for specific types of applications. Despite recent researchers who have implemented other techniques into existing libraries and found dramatic performance improvements (see Chapter 3), the OpenMP standard still lists only the three mentioned algorithms. On top of that, recent works employed the new techniques mostly on libgomp, letting more research to be done with LLVM's libomp.

In this thesis, we implement more advanced DLS techniques into the LLVM OpenMP runtime library, libomp [7], that is used with the Clang compiler. These additional methods can then be used by any programmer to parallelize their programs. In order to gain insights into the performance with different types of loops, the newly implemented techniques are evaluated on a shared memory high-performance computing node. For this purpose, benchmarks from suites like EPCC [8], Rodinia [9], OmpSCR [10], NAS [11] and SPEComp2012 [12] are chosen.
The results show that there is no superior technique for every case. Depending on the application, loop characteristics and system, one technique can outperform every other.

The remaining of this thesis is structured as follows. Chapter 2 shortly explains what parallelism is, gives an overview of many scheduling techniques and summarizes OpenMP and its LLVM runtime. In Chapter 3, related work is discussed. Chapter 4 explains the current LLVM implementation and shows what needs to be changed for the extensions. Implementation details are given in Chapter 5. Chapter 6 discusses a few performance optimization decisions during the implementation. Chapter 7 contains the validation of the implemented techniques and Chapter 8 presents the results followed by the conclusion.

2 Background

This chapter gives an overview of many scheduling techniques. Starting by a brief explanation about parallelism in Section 2.1, the techniques itself in Section 2.2 and an introduction to OpenMP in Section 2.3.

2.1 Parallelism

To better understand the ideas and goals of loop scheduling techniques, it is helpful to remember what parallelism is and where it is applicable. In computer science, parallelism is the simultaneous execution of calculations, tasks and processes or threads. There is a distinction between software and hardware parallelism. Both of them are important and must work together to fully exploit the true potential of parallelism. Processors of today mostly come with rich hardware parallelism support, such as multiple cores, which can execute different tasks simultaneously. Software developers, however, must evolve their solutions in order to utilize the given potential in current hardware systems.
The process of parallelization includes the decomposition of large computational tasks into smaller ones, the analysis of dependencies between the decomposed tasks and their scheduling onto the target computing system. In this thesis, we focus on loop scheduling, where portions of a loop's iterations are assigned to different PUs (e.g., cores of a CPU[1]) for parallel execution.

2.1.1 Shared Memory

This thesis focuses on implementing loop scheduling techniques and running parallel loops on shared memory systems only. These systems differ from distributed memory machine models in the way how PUs are connected to the memory. In shared memory systems, all PUs are connected to the same main memory which they share. In the distributed memory model, the PUs have their own local memory, that is separated from other PUs. Thus, they need to communicate with other PUs to share data. The latter model is not discussed in

[1] Central Processing Unit

this thesis.

2.1.2 Multithreading

Multithreading is a way of how an application can use multiple threads, supported by the operating system, to execute operations on one PU (e.g., core of a CPU) or simultaneously on multiple PUs. The difference between multiprocessing and multithreading is that threads of an application use the same address space and can access on the same data, wherein processes have their own address space, thus, they are considered to be heavier than threads. OpenMP, discussed in Section 2.3, uses threads, which makes multithreading the prominent process model of this thesis.

2.2 Loop Scheduling

Loops are the dominant source of parallelism. Large programs, especially those of scientific areas which compute simulations of, for example, physical interactions of bodies [13], contain one or more large loops that consume most of the computation time. Parallelizing those heavy loops can dramatically speedup the program execution time. By parallelizing loops, we mean the decomposition of a loop in blocks of iterations, i.e., smaller tasks, and the scheduling of these blocks to available PUs. The process of parallelization, however, has one constraint that must be analyzed. The dependency analysis. To be able to parallelize a loop, the iterations must be independent of each other so that the order of execution does not change the final result. The programmer must take care of the dependencies himself. In this thesis, we only focus on loop scheduling and assume that the dependency analysis is made correctly by the programmer.
Scheduling in computer science is defined as the ordering of computation and data in space and time. In this case, the distribution of loop iterations over PUs and time. The parallel execution of iterations among the available PUs increase the performance of the program. However, loop iteration execution times can vary because of conditional statements inside the loop or input values. These variations can lead to uneven execution finishing times of PUs, also called load imbalance. If one PU takes much more time to finish its portion of iterations than the other PUs, the idling PUs and their potential computation power are wasted. Scheduling techniques try to balance the load among the PUs in order to produce even finishing times and reduce wasted potential. However, scheduling involves overhead which can lead to bad performance. In general, there is a fundamental trade-off in loop scheduling between load balance and scheduling overhead. Depending on the loop characteristics, one scheduling technique fits better than the others to reduce overall execution time. There are many different approaches of realizing loop scheduling. The following sections give an overview of static and dynamic loop scheduling techniques. Table 2.1 declares many of the common variables that are used in the following sections.

Table 2.1: Declaration of common variables, which are used in the loop scheduling techniques' descriptions.

Variable	Description
P	The number of PUs.
N	The number of iterations.
Cs	The chunk size.
R	The number of remaining iterations.
μ	The mean value of iteration execution times.
σ	The standard deviation of iteration execution times.
h	The scheduling overhead time.

2.2.1 Static Techniques

Static loop scheduling techniques take scheduling decisions before the execution of an application. Fixed size chunks are given to PUs before the execution of the loop. Static techniques produce the least amount of scheduling overhead time. They favor regular loops with constant-length iterations. Irregular loops can produce serious load imbalance when parallelized with static techniques because of uneven finishing times.

2.2.1.1 Static Chunking

One example of static loop scheduling techniques would be *Static Chunking* (SC) , in which, a loop is decomposed into P equal sized chunks of iterations. The chunk size

$$Cs = \frac{N}{P} \tag{2.1}$$

is computed prior the execution of the loop. An example of SC is depicted in figure 2.1. It illustrates the bad case of static techniques, where iteration execution times vary and, therefore, the PUs finish unevenly.

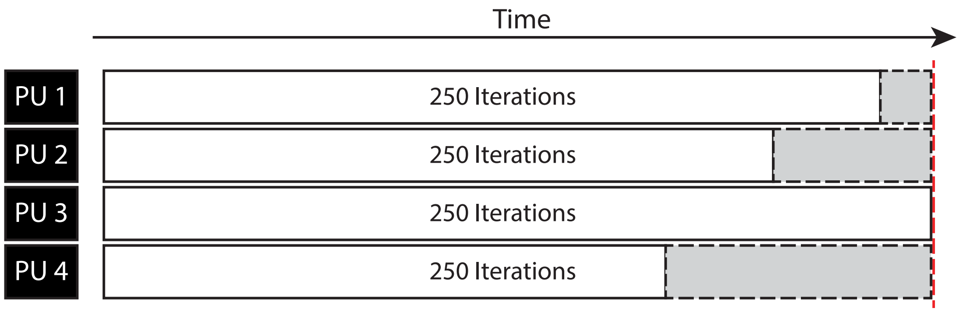


Figure 2.1: Example illustration of SC with $P = 4$ and $N = 1000$. White areas show the computation time. Shaded areas depict idle times (i.e., inefficiency). The dashed red line marks the overall finishing time of loop execution.

2.2.2 Dynamic Techniques

Dynamic scheduling techniques have a major difference when compared to static methods. The scheduling decisions are made during application execution. In other words, idling PUs dynamically grab iterations during runtime until the loop is computed. This can be realized either in a centralized fashion, e.g., a master PU that assigns new tasks to the worker PUs, or in a decentralized way, in which all of the PUs reassign tasks by themselves using a common pool of iterations. DLS methods are also differed to the categories *Nonadaptive DLS* (NADLS) techniques and *Adaptive DLS* (ADLS) techniques.

Nonadaptive DLS techniques are dynamic loop scheduling techniques, which use pre-computed information or data obtained prior execution time to make scheduling decisions during runtime. Information obtained prior loop execution does not change during runtime.

Adaptive DLS techniques are dynamic loop scheduling methods, which adapt their scheduling decisions to information obtained during runtime.

2.2.2.1 Self-Scheduling

SS [14] is one of the oldest DLS techniques. It assigns a single new iteration to an idling PU until all of the iterations are computed. The chunk size is

$$Cs = 1. \tag{2.2}$$

SC and SS mark the extremes regarding the fundamental trade-off in loop scheduling techniques. Where SC provides the least amount of scheduling overhead time with the cost of the worst load balance, SS come with the best load balance possible while producing the biggest amount of scheduling overhead due to the many scheduling states. Figure 2.2 illustrates an example of SS. This example does not stem from a simulation or real scenario but it shows

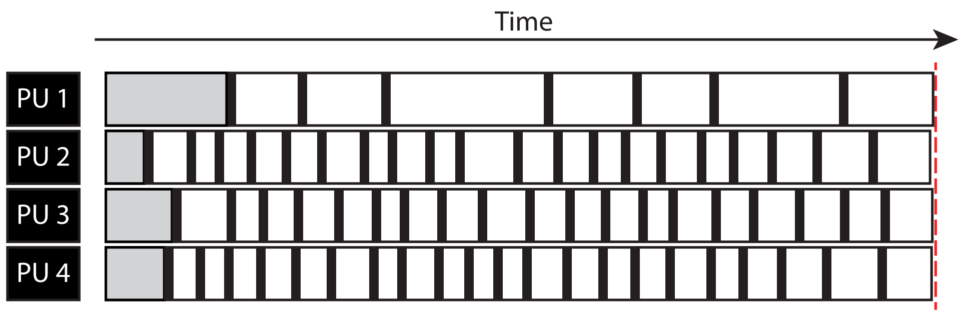


Figure 2.2: Example illustration of SS with $P = 4$ and $N = 67$. White segments show the computation time of individual iterations. Black segments illustrate scheduling overhead time (fixed h for this illustration). Shaded segments mark load prior to the loop execution. The dashed red line marks the overall finishing time of loop execution. Note: This is not a real simulation.

a representative case where iteration execution times can vary and PU 1 is slower. The idea of SS is to even out PUs' finishing times even with highly irregular loops or systemic load imbalances. While PU 1 computes only 7 iterations, PUs 2-4 are executing more than twice of this amount each. The PUs' finishing times are almost the same but SS comes with the cost of high scheduling overhead. In [14], they claim that scheduling overhead can be reduced if SS is implemented in a decentralized model with a common variable to get loop iterations.

2.2.2.2 Fixed Size Chunking

In *Fixed Size Chunking* (FSC) [15], the idea is to reduce the immense scheduling overhead of SS by scheduling chunks of iterations instead of a single one. The chunk size is

$$Cs = \left(\frac{\sqrt{2}Nh}{\sigma P \sqrt{\log P}} \right)^{\frac{2}{3}}. \tag{2.3}$$

The formula stems from mathematical analysis and tests to find an optimal size for reducing scheduling overhead while still providing a good load balance. The chunks are added to a common pool or queue from which idling PUs can take their chunks of iterations. This is the first method discussed in this thesis, that involves the standard deviation of iteration execution times obtained from previous runs of the same loop. In [15], assumptions are made, that the scheduling overhead h is independent of the amount of iterations scheduled at once.

2.2.2.3 Guided Self-Scheduling

GSS [16] tries a different approach by scheduling decreasing chunk sizes across the PUs instead of a fixed size. The goal is to reduce the scheduling overhead time of SS with less chunks and still provide a good load balance. One assumption made in [16], is that PUs have unequal starting times caused by, for instance, other work prior to the loop calculation. To counteract this problem, they have designed decreasing chunk sizes calculated by

$$Cs_i = \left\lceil \frac{R_i}{P} \right\rceil, \tag{2.4}$$

where R_i denotes the remaining number of iterations for the ith chunk and $R_1 = N$. This method does not involve the values μ and σ, thus, profiling of previous runs is not necessary in contrast to FSC. However, a big first chunk size could lead to bad load balance if the first PU takes too much time for calculating the first and biggest chunk.

2.2.2.4 Trapezoid Self-Scheduling

Trapezoid Self-Scheduling (TSS) [17] wants to extract the advantage of GSS and at the same time provide a simple linear function for decreasing chunk sizes. Furthermore, it takes two inputs from the user which specify the size of the first chunk, f, and last chunk l. The chunk size is then calculated according to equations 2.5.

$$\begin{aligned} A &= \left\lceil \frac{2N}{f+l} \right\rceil, \\ \delta &= \frac{f-l}{A-1}, \\ Cs(1) &= f, \\ Cs(t) &= Cs(t-1) - \delta. \end{aligned} \tag{2.5}$$

In the above equations, t denotes the number of the current scheduling operation (also called chore) and A is the number of chores (i.e., chunks). The authors in [17] give a general suggestion for the first chunk size with $f = \frac{N}{2P}$. Furthermore, they claim that the linearity makes TSS more simple and efficient to implement, which reduces scheduling overhead.

2.2.2.5 Factoring

Factoring (FAC) , a generalized version of GSS and FSC, was presented in [18]. The idea of FAC is to be more robust and resistant to iteration execution time variance than GSS. FAC also makes use of decreasing chunk sizes for better load balancing. In contrast to earlier methods, this technique schedules iterations in batches of P equal size chunks. For each batch, one chunk size is calculated according to equations 2.6 and then P chunks of the calculated size are placed at the head of the scheduling queue.

$$\begin{aligned} Cs_j &= \left\lceil \frac{R_j}{x_j P} \right\rceil, \\ R_0 &= N, R_{j+1} = R_j - PCs_j, \\ b_j &= \frac{P}{2\sqrt{R_j}} \frac{\sigma}{\mu}, \\ x_0 &= 1 + b_0^2 + b_0\sqrt{b_0^2+2}, \\ x_j &= 2 + b_j^2 + b_j\sqrt{b_j^2+4}, j > 0. \end{aligned} \tag{2.6}$$

j denotes the batch index. One batch is calculated and placed after the previous batch is scheduled. FAC uses a probabilistic analysis to calculate the chunk size. More precisely, the number of iterations per batch is determined by estimating the maximum portion of the remaining iterations R, that have a high probability of being calculated before the optimal time, $\mu\frac{N}{P}$, of all the remaining iterations, when the iterations in each batch are equally divided into P chunks. This is also why the method is called `Factoring` because each batch gets a fixed ratio of R. The relation to GSS and FSC can be described as follows. FAC is like GSS, when each batch contains only one chunk, and like FSC, when there is only one batch.
A simplified version of FAC for practical use, called FAC2, is presented in [18]. FAC2 sets $x = 2$, which leads to the chunk size

$$\begin{aligned} Cs_j &= \left\lceil \frac{R_j}{2P} \right\rceil \\ &= \left\lceil \left(1 - \frac{1}{2}\right)^j \frac{N}{2P} \right\rceil \\ &= \left\lceil \left(\frac{1}{2}\right)^{j+1} \frac{N}{P} \right\rceil. \end{aligned} \tag{2.7}$$

Determining x for each batch is difficult in practice, because precise knowledge of the mean and standard deviation is required. FAC2 solves this problem. An illustrative example can be seen in figure 2.3.
FAC is extremely general and robust to different variances of iterations. It behaves, depending on whether σ is high or low, like SS or static.

2.2.2.6 Weighted Factoring

Weighted Factoring (WF) [19] is very similar to FAC. However, this strategy takes PU speeds into consideration for calculating the chunk sizes. The idea is to dynamically assign

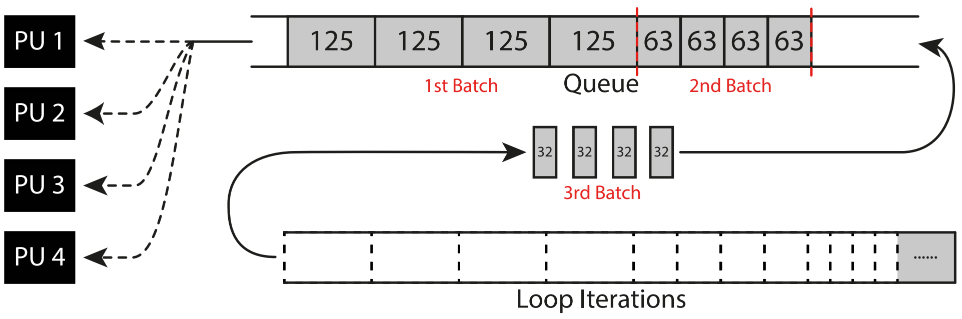


Figure 2.3: Example illustration of FAC2 with $P = 4$ and $N = 1000$. In this example, a common variable or queue is used for scheduling.

decreasing size chunks of iterations, like in FAC, to PUs in proportion to their processing speeds. In conclusion, each PU is associated with a weight w that represents its relative speed. These weights are normalized and add up to the number of available PUs. After the batch and chunk size are calculated like in FAC, the chunks of a batch are multiplied by the weights and assigned to the corresponding PUs. The following equation 2.8 shows the chunk size of batch j for PU i.

$$Cs_{ij} = w_i \times Cs\_factoring_j \quad \text{and} \quad \sum_{i=1}^{P} w_i = P. \tag{2.8}$$

The weights are estimated by benchmarking the system a priori. During runtime, the weights stay constant. This strategy is meant for heterogeneous work-stations with different PU speeds and system-induced impact to the performance.

2.2.2.7 Taper

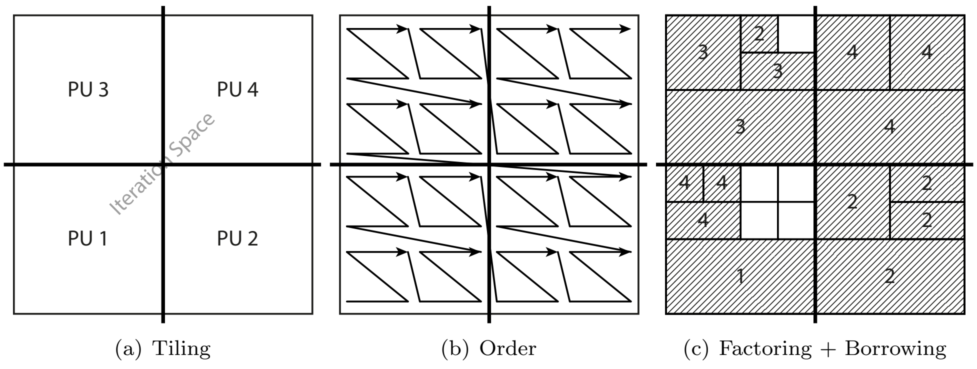
Based on GSS, *Taper* (TAP) [20] tries to achieve optimal load balance, while scheduling the largest possible chunk size to decrease the number of chunks scheduled and, with that, the scheduling overhead. It differs from GSS by taking the mean μ and standard deviation σ of iteration times into account to get a better load balance. The chunk size formula, given in equations 2.9, is derived from probabilistic analysis to achieve an optimum for the above idea.

$$\begin{aligned} Cs_i &= \max\left\{ Cs_{min}, \left\lceil T_i + \frac{v_\alpha^2}{2} - v_\alpha \sqrt{2T_i + \frac{v_\alpha^2}{4}} \right\rceil \right\}, \\ T_i &= \frac{R_i}{P}, \\ v_\alpha &= \frac{\alpha\sigma}{\mu}. \end{aligned} \tag{2.9}$$

In the above equations, i is the chunk index, Cs_{min} denotes the minimum chunk size and α is a scaling factor of the *coefficient of variation* (c.o.v.) , that is found empirically [20]. It is influenced by the overhead time and the ratio of N to P. Furthermore, TAP is GSS, when $\sigma = 0$.

2.2.2.8 Fractiling

Fractiling (FRAC) [13][21] is a combination of FAC and tiling. Tiling partitions the iteration space into regions of suitably granularity. FRAC combines FAC's idea to minimize load imbalance and scheduling overhead via allocation of work in decreasing-size chunks, and tiling, to maximize data locality. This method is especially suited, and designed, for very irregular loops like in N-Body simulations [13].
The process in FRAC can be described as follows. During initialization, the iteration space is divided into P tiles and each of them is assigned to a PU. After the initial tiling process, each PU's tile is divided into two half-sized subtiles via bisection. The subtiles are also called fractiles. Every PU then starts working on its first subtile and repeatedly bisects its next subtile into two smaller subtiles and, again, works on the first half. This is done by every PU until all of the work in its initially assigned tile is done. Due to the shuffle row-major tiling and allocation order of (sub)tiles, the execution order and shape of fractals are self-similar, which brings some advantages, like data locality. A PU that finishes its tile early, borrows decreasing sized subtiles of unallocated work from other, slower PUs to balance loads. The fractiling process is described in Algorithm 1. Figure 2.4 shows an illustrative example of FRAC.



(a) Tiling (b) Order (c) Factoring + Borrowing

Figure 2.4: Illustration of Fractiling with 4 PUs and 64 iterations. Figure 2.4(a) shows how the iteration space is divided into P tiles with 16 iterations each. The order of tiling and allocation is depicted in 2.4(b). In figure 2.4(c), the shaded rectangles represent calculated chunks by the indicated PUs. The tiles are subsequently divided by 2 after a batch has completed. You can see that each batch contains exactly $P = 4$ equal-sized chunks (subtiles), except for the smallest rectangles which are individual iterations. This is exactly where you can see the similarity to FAC. Lastly, fast PUs, like PU 2 and 4 in the example, start to help slower PUs, here PU 1 and 3, after finishing their own tiles.

2.2.2.9 The Bold Strategy

The Bold Strategy (BOLD) [22] is the first adaptive DLS technique described in this thesis. It is a bolder version of FAC and further development of TAP. As in TAP, it uses the mean and standard deviation of iteration execution times as well as an estimate of scheduling overhead time. BOLD takes multiple input variables and then, during runtime, it creates new variables and adjusts old ones, based on new state information, for an adaptive chunk

Algorithm 1 Fractiling [21]

```
1: divide iteration space into $P$ tiles of size $\frac{N}{P}$
2: assign one for each PU in shuffled row-major numbering
3: for all PU do                                                    ▷ in parallel
4:     allocate the fractile corresponding to half of the initial PU assignment
5:     while there are fractiles not done on the level do
6:         do the allocated fractile
7:         enter a mutex lock
8:         while there is a fractile in the initial assignment to do do
9:             successively allocate the next fractile in decreasing chunk size and in shuffle order
10:        end while
11:        while there are remaining fractiles to do in other PU assignments do
12:            successively allocate a fractile in decreasing chunk size and in shuffle order
13:        end while
14:        exit the mutex lock
15:    end while
16: end for
```

size calculation. The driving idea behind the final strategy was to increase early chunk sizes in order to reduce scheduling overhead, while considering the risk of a potential big chunk that could last until the end and, thus, lengthen the overall executing time. The strategy derives from probabilistic analysis of that idea. It is designed for loops with algorithmic (e.g., conditional statements in loop body) and system-induced (cache misses and other system interferences) variance. BOLD is intended to be implemented in a centralized model with a master who assigns chunks of iterations to requesting PUs. Assumptions are made that the scheduling overhead time h is a fixed delay, independent of the number of iterations scheduled at once or the amount of PUs requesting new work at once. Furthermore, the authors note that the calculation might produce more overhead because of its complexity. The algorithms 2 and 3, which show the strategy, need some explanation for the used variables and how they are adapted during runtime [22]:

`boldM` The number of iterations that either are unassigned or belong to chunks currently under execution [22]. It is initialized to N. This variable has to be adjusted during runtime in the following way. Whenever a PU completes a chunk of size Cs, $boldM$ is decremented by Cs [22].

`totalspeed` "Indicates the expected number of iterations completed per time unit, taking the allocation delay into account, and tends to lie slightly below $\frac{P}{\mu}$." [22]. This variable is initialized to 0. It is adjusted whenever a PU starts or finishes working on a chunk. At the start of a chunk of size Cs, the PU increments $totalspeed$ by $\frac{Cs}{Cs\mu+h}$, and after the execution of the chunk, it decrements $totalspeed$ by the same value. This variable is used to maintain $boldN$.

`boldN` This variable is an estimate of the number of iterations that have not yet been executed [22]. It is initialized to N. Furthermore, it assumes that while a PU is executing a chunk, it makes steady progress at exactly one iteration every μ time units. Maintaining $boldN$ during runtime requires $totalspeed$ and three points in time,

t_1, t, t_2. Figure 2.5 [22] describes the mentioned points in time. To maintain $boldN$,

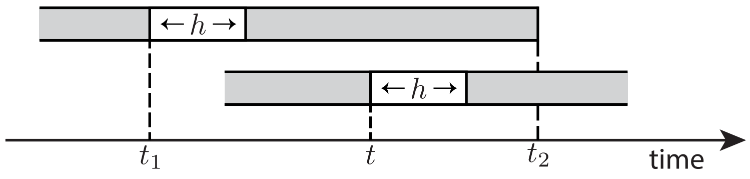


Figure 2.5: Description of the time points t_1, t, t_2 used to update $boldN$. Computation time is shown shaded. At t_1, the processing of a new chunk of size Cs begins (including overhead time for scheduling). The processing ends at time t_2. t is defined as the last point in time before t_2 at which a chunk is completed or a new one is allocated.

the variable is adjusted at time t_2, before $totalspeed$ is updated, by

$$boldN_{\text{new}} = boldN_{\text{old}} - \left(\underbrace{(t_2 - t)\, totalspeed}_{\text{collective progress since } t} + \underbrace{Cs - \frac{(t_2 - t_1)\, Cs}{Cs\mu + h}}_{\text{correction term}} \right). \tag{2.10}$$

Q The number of remaining unassigned iterations per PU.

Algorithm 2 Bold initialization [22]

```
1:  $a = 2\left(\frac{\sigma}{\mu}\right)^2$
2:  $b = 8a \ln(8a)$
3:  **if** $b > 0$ **then**
4:      $ln\_b = \ln(b)$
5:  **end if**
6:  $p\_inv = \frac{1.0}{P}$
7:  $c_1 = \frac{h}{\mu \ln(2)}$
8:  $c_2 = \sqrt{2\pi c_1}$
9:  $c_3 = \ln(c_2)$
10: $boldM = N$
11: $boldN = N$
12: $totalspeed = 0$
```

2.2.2.10 Adaptive Weighted Factoring

Adaptive Weighted Factoring (AWF) [23] is similar to WF but addresses the limitation of the weights not being adapted during computation. Furthermore, it does not need prior knowledge of system load. Therefore, profiling is not necessary. AWF is designed for time-stepping applications, like N-Body simulations, where each time step involves one heavy loop. Weights are adjusted only after each time step, thus, not during loop execution. AWF is still described here since there are variations based on it which allow non-time-stepping applications. The variations are discussed in the following Section 2.2.2.11. In AWF, the cumulative performance of each PU from all the previous steps is used for determining the weights. This technique incorporates both loop characteristics and PU speeds in calculating the chunk sizes.

Algorithm 3 Bold routine for subsequently determining chunk sizes [22]

```
1: function CalculateChunkSize($P, N, R, a, b, p\_inv, ln\_b, c_1, c_2, c_3, boldM, boldN$)
2:     $Q = \frac{R}{P}$
3:     if $Q \leq 1$ then
4:         return 1
5:     end if
6:     $r = \max\{R, boldN\}$
7:     $t = p\_inv \times r$
8:     $ln\_Q = \ln(Q)$
9:     $v = \frac{Q}{b+Q}$
10:    $d = \frac{R}{1+\frac{1}{ln\_Q}-v}$
11:    if $d \leq c_2$ then
12:        return t
13:    end if
14:    $s = a(\ln(d) - c_3)\left(1 + \frac{boldM}{rP}\right)$
15:    if $b > 0$ then
16:        $w = \ln(v \times ln\_Q) + ln\_b$
17:    else
18:        $w = \ln(ln\_Q)$
19:    end if
20:    return $\min\left\{t + \max\{0, c_1 w\} + \frac{s}{2} - \sqrt{s\left(t + \frac{s}{4}\right)}, t\right\}$
21: end function
```

In a master-worker model, after each time step, the PUs send their total execution time to the master PU, not including the scheduling time. The master then computes the weights for all PUs. For this, it first determines the weighted average ratio

$$\pi_i = \frac{\left(\sum_{j=1}^{s} j \times t_{ij}\right)}{\left(\sum_{j=1}^{s} j \times n_{ij}\right)}, \tag{2.11}$$

which gives the average ratio of execution time per iterations, $\frac{t_{ij}}{n_{ij}}$, of a step j, of all the executed steps s on PU i. More recent steps are weighted higher to produce a better adaptation of very recent workloads. The next step is to compute the average weighted average ratio

$$\bar{\pi} = \frac{\sum_{i=1}^{P} \pi_i}{P}, \tag{2.12}$$

of all PUs. Now, the raw weight of PU i is defined as

$$\rho_i = \frac{\bar{\pi}}{\pi_i}. \tag{2.13}$$

In order to fulfill the requirement of WF, where weights must add up to the number of P, the master needs to normalize the raw weights ρ_i. Equation (2.14) shows the normalized weight w_i for PU i using the above variables.

$$w_i = \frac{\rho_i \times P}{\hat{\rho}}, \quad \text{where} \quad \hat{\rho} = \sum_{i=1}^{P} \rho_i. \tag{2.14}$$

The weights are initially set to 1 and then adjusted after each step. Finally, like in WF, the master can use the determined weights, which do not change during a time step, to weight the chunk sizes obtained from FAC and calculate the final chunk size

$$Cs_{ij} = w_i \times Cs\_factoring_j \quad \text{and} \quad \sum_{i=1}^{P} w_i = P \tag{2.15}$$

for a PU i and batch j. The following variants of AWF provide the possibility to adapt during a loop.

2.2.2.11 Adaptive Weighted Factoring Variants

There exist variants [24] of the above described technique AWF from Section 2.2.2.10. In this part, four variations of AWF, AWF-B, AWF-C, AWF-D and AWF-E, are shown. All of them have a common goal. They address the limitation of AWF to rely on time-stepping applications, where the adaptation happens only after each step. The variants allow adaptation during loop execution. Depending on the chosen variant, the PU weights are adjusted less or more frequently. The calculation of chunk sizes is very similar to AWF but the variants use a modified formula for the weighted average ratio

$$\pi_i = \frac{\left(\sum_{j=1}^{s_i} j \times t_{ij}\right)}{\left(\sum_{j=1}^{s_i} j \times n_{ij}\right)}. \tag{2.16}$$

Unlike in AWF, the modified version above determines the weighted average ratio of the executed chunks j, $1 \leq j \leq s_i$, by PU i instead of previous time steps. This is exactly the modification which allows updates during a loop. Initially, the weights are set to 1 for all PUs like in AWF and an arbitrarily chosen first batch size of $\beta_0 \times N$, $0 < \beta_0 < 1$, is selected like in AF to determine the initial chunk size

$$Cs_{i1} = n_{i1} = \beta_0 \times \frac{N}{P} \tag{2.17}$$

for a PU i. From here on, the succeeding chunks are determined differently by one of the following variants:

`AWF-B` schedules the remaining iterations by batches. The weights are adjusted after each batch based on timings from previous chunks.

`AWF-C` schedules the remaining iterations by chunks, similar to AF, instead of batches. The idea of this variation is to address a possible issue of AWF-B (as well as FAC, WF and AWF), where faster PUs which already have computed their portion of the batch could be assigned remaining chunks of less-than-optimal size from the current batch. The reason is that in these methods, the chunk sizes are fractions of the current FAC batch size which, once scheduled, do not change. AWF-C tries to solve this issue by recomputing a new batch size each time a PU requests for work and before applying AWF for weight calculation. This modification results in faster PUs being assigned larger chunks from all the remaining iterations and not just from the ones left in current batch.

`AWF-D` is like AWF-B but the execution time of iterations of a chunk j, t_{ij}, is redefined as the total chunk time. This not only includes the execution time but also the time spent by the PU in doing tasks associated with the execution of a chunk (e.g., bookkeeping).

AWF-E is like AWF-C but uses to total chunk time as in AWF-D.

2.2.2.12 Adaptive Factoring

The last adaptive DLS technique discussed in this thesis is *Adaptive Factoring* (AF) [25][26]. As the name indicates, it is based on FAC. The difference is that AF relaxes the requirement in FAC, where mean μ and standard deviation σ are known a priori and additionally that they are the same on all PUs. The statistical values of μ and σ are calculated and adjusted during runtime. AF is thus a more generalized technique than FAC or WF and it is advantageous if the mean and variance are unknown and vary during runtime. Besides the adaptivity and generality, AF uses, like in FAC, a probabilistic model to calculate chunk sizes and dynamically allocate chunks of iterations to PUs such that the average finishing time for completion of the chunks occurs before the optimal time, $\mu\frac{N}{P}$, of the whole remaining task [25]. In other words, the expected finishing time of the current batch has a high probability to occur before the optimal finishing time of the whole remaining task. In direct comparison with WF, where weights are statically assigned to each PU, AF does not use fixed weights but dynamically computes the size of a new chunk for a PU based on its performance information gathered from recently executed chunks. In other words, AF dynamically weights chunk sizes for individual PUs based on their recent performance.
AF can be implemented with a master-worker model in which the request messages of workers contain updated performance data (μ and σ) of recently executed chunks [26]. The master uses this information to compute the chunk sizes with

$$\begin{aligned} Cs_i^{(n)} &= \frac{D_n + 2T_nR_{n-1} - \sqrt{D_n^2 + 4D_nT_nR_{n-1}}}{2\hat{\mu}_i}, && n > 1 \\ \text{and} \quad Cs^{(1)} &\geq 100, && n = 1 \end{aligned} \tag{2.18}$$

for a PU i and step (or batch) n. The variables D and T incorporate the latest estimator for the means and standard deviations of every PU. They are calculated as shown in (2.19).

$$D_n = \sum_{i=1}^{P} \frac{\hat{\sigma}_i^2}{\hat{\mu}_i}, \quad T_n = \left(\sum_{i=1}^{P} \frac{1}{\hat{\mu}_i} \right)^{-1}, \quad n > 1. \tag{2.19}$$

The remaining iterations R_n after step n are calculated as

$$\begin{aligned} R_0 &= N, \\ R_1 &= R_0 - PCs^{(1)}, \\ R_n &= R_{n-1} - \sum_{i=1}^{P} Cs_i^{(n)}, \quad n > 1. \end{aligned} \tag{2.20}$$

Since AF does not need a priori profiling, it first estimates the mean and standard deviation for each PU i in an arbitrarily sized initial batch (step 1) with P chunks of size $Cs^{(1)}$. For this, the PUs have to record their finishing times X_{ij} of each iteration $j, 1 \leq j \leq Cs^{(1)}$. The initial estimators for the mean $\hat{\mu}_i$ and standard deviation $\hat{\sigma}_i$ of a PU i are then calculated with

$$\hat{\mu}_i = \frac{\sum_1^n X_{ij}}{Cs^{(1)}} \quad \text{and} \quad \hat{\sigma}_i = \left(\frac{\sum_1^n X_{ij}^2 - Cs^{(1)}\hat{\mu}_i^2}{Cs^{(1)} - 1} \right)^{\frac{1}{2}}. \tag{2.21}$$

Algorithm 4 shows the steps in AF for how chunk sizes are calculated and iterations are allocated. Step 1 allocates the iterations in batch. Afterwards, there is no need for allocating

Algorithm 4 AF algorithm for chunk size calculation and allocation [25].

```
 1: procedure AdaptiveFactoring
 2:     $n \leftarrow 1$                                  ▷ step number
 3:     AFInitialize                  ▷ step 1, there are $R_1$ iterations left
 4:     while $R > 0$ do
 5:         $n \leftarrow n + 1$
 6:         AFAllocate($n$)           ▷ step $n$, there are $R_n$ iterations left
 7:     end while
 8: end procedure
 9:
10: procedure AFInitialize
11:     assign to each PU $Cs^{(1)}$ iterations, with $Cs^{(1)} \geq 100$
12:     record finishing times $X_{ij}$ of each iteration $j$ for each PU $i$
13: end procedure
14:
15: procedure AFAllocate($n$)   ▷ can be executed for any individual PU $i$ requesting
16:     estimate $\mu$ and $\sigma$ for each PU $i$ using information of previous steps and (2.21)
17:     assign $Cs_i^{(n)}$ iterations to PU $i$ using (2.18)
18:     record finishing times $X_{ij}$ for each iteration $j$ in every PU $i$
19: end procedure
```

in batches. Whenever a PU finishes its chunk, a new one of size (2.18) is immediately allocated by the master.
When comparing AF to AWF and its variants, it is important to mention that AF introduces more overhead because of the intensive time measurements on an iteration level rather than batch or chunk levels.

2.3 OpenMP

OpenMP is a standard for shared memory parallel programming. It consists of directives and pragmas, which collectively define the specification of the OpenMP Application Programming Interface (OpenMP API). In order to use OpenMP, a compiler is required that supports the OpenMP specification and implements the API. Many popular compilers, like GCC [5][4], Intel C++ Compiler [27] and LLVM Clang [28], already support the specification [2] and can be used for parallelizing programs. Compilers with OpenMP support can compile one or many of the languages C, C++ and Fortran [1].
OpenMP uses the shared memory programming model, i.e., execution happens on one node with same address space. Directives or pragmas can be elegantly used in the source code to implicitly parallelize parts of a program. The directives tell the compiler how statements are to be executed and which parts are parallel. The compiler then generates multithreaded code by reading the directives. There are many constructs in OpenMP, such as parallel regions, work-sharing, variable scoping, critical regions and synchronization, to parallelize a program but we focus on the work-sharing part, where a loop and its iterations are split among threads. Parallelizing loops is one of the most popular features of OpenMP. Doing this only

requires one single line in C/C++ before a for-loop, namely, `#pragma omp parallel for`. The user can also set clauses within a pragma to, for example, select whether or not threads have their own copy of a variable, or how a loop should be scheduled. The exact syntax of the work-sharing-loop construct for C/C++, as described in the specification [1], is

#pragma omp for *[clause[[,]clause]...]new-line*
for-loops

where the schedule clause corresponds to **schedule**(*[modifier[, modifier]:]kind[, chunk_size]*). The modifiers can be used to specify whether chunks are executed in increasing logical iteration order or not. Our focus lies on the `kind`, which specifies the scheduling algorithm. Which values currently are available for `kind` and what they stand for is described in the following subsection.

2.3.1 Scheduling in OpenMP

OpenMP lists three loop scheduling techniques in the specification [1], however, there are many more which are not listed. Therefore, available OpenMP implementations, like the ones mentioned in Subsection 2.3.2, are only required to implement the listed techniques in the specification. These are `static`, `dynamic` and `guided`. On top of that, the user must specify a chunk size within the pragma. Based on that size, the chosen technique, for instance `static`, statically schedules blocks of iterations of given size to each PU prior to loop execution. The option `dynamic` dynamically schedules chunks of iterations of specified size to idling PUs during runtime. Lastly, `guided` uses a dynamic scheduling approach with decreasing chunk sizes down to the specified size. These three techniques are similar to the explained techniques in Section 2.2, Static, SS and GSS, but the exact implementation depends on the used OpenMP library. Furthermore, the schedule selection can be postponed to be chosen during runtime by using the kind `runtime`. An example of it looks like

#pragma omp for schedule(runtime).

Every loop with the above schedule clause will then be scheduled by the strategy which is set in the environment variable `OMP_SCHEDULE`. The value of this variable takes the form *[modifier:]kind[, chunk]*.

2.3.2 LLVM OpenMP Runtime Library

LLVM's Clang supports OpenMP 3.1 by default since version 3.8.0 [7]. The LLVM runtime, libomp, stems from Intel's open source OpenMP runtime [29] and contains almost the exact same code as Intel has merged its open-source library to the LLVM project where further development takes place [30]. While this library is compatible with Intel, GCC and LLVM's compilers, GCC's libgomp is not compatible with Clang. The fact that libomp is Intel and LLVM's production library for OpenMP while supporting GCC, makes it very significant. Since this thesis is focusing on the LLVM compiler infrastructure, an overview of the development process with LLVM is given in figure 2.6 [29]. The compile-time involves compiling

C/C++ source code including OpenMP directives using Clang which is a C language family compiler front-end for LLVM. Clang uses the LLVM compiler infrastructure, a compiler tool chain, as its back-end to finally compile the source code into a binary file. During runtime, the application uses libomp for routine calls. To link the library, the compile flag `-fopenmp` must be used. It is also possible to link a runtime explicitly by its name with `-fopenmp=<library-name>`.

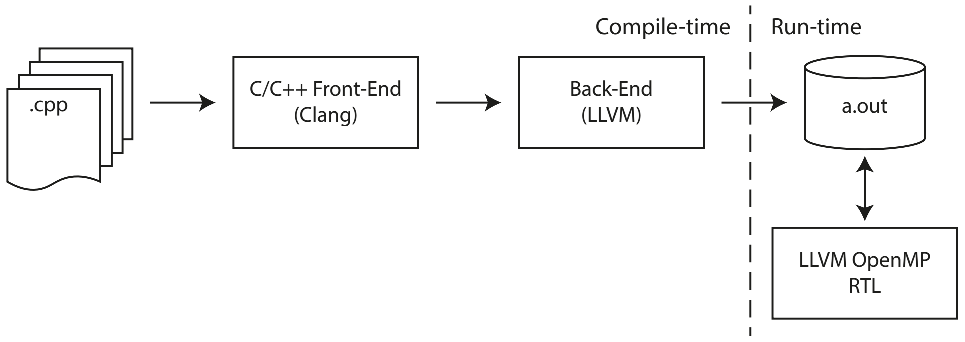


Figure 2.6: The process of compiling C/C++ source code with OpenMP and LLVM. The runtime library handles calls from the binary during runtime.

Once a binary is produced, the environment variables indicate, for example, which runtime library to use or what kind of scheduling technique should be picked if the programmer has set `schedule(runtime)` inside the pragma. The path to the library can be specified in the environment variable `LD_LIBRARY_PATH`. A recompilation is not needed if this path changes, which makes it easy to switch between different implementations of the runtime library. The number and type of available scheduling techniques depend on the actual implementation. For instance, the current checked out code of libomp only implements `static`, `guided`, `dynamic` and `trapezoidal` loop scheduling techniques. As for now, the latter technique is not yet listed in the library's latest manual [3], since the manual has not been built for three years from now. The absence of many other DLS techniques in libomp is the gap that we want to fill in this thesis by implementing additional techniques.

3 Related Work

In this chapter, related works from the past are discussed. Since this thesis focuses on the implementation of additional loop scheduling techniques into an OpenMP runtime library, it is important to see what others have done in that area for existing OpenMP implementations. All the above methods from Section 2.2 have already been implemented and tested but none of them, except for similar versions of SC, SS, GSS and TSS, have been implemented into the LLVM OpenMP runtime library. Most of them have not even been implemented in any existing OpenMP runtime library since the OpenMP specification does not list more than three methods. However, past research projects have implemented new techniques into existing OpenMP runtime libraries, such as GCC's libgomp [4] and evaluated the results.

Officially, libgomp provides only `static`, `dynamic` and `guided` scheduling techniques. The work by Buder P. [31], which is the closest to this thesis, implemented and tested six additional DLS techniques in libgomp. Additionally, a related paper to Buder's work was published by Ciorba et al. [32]. The newly implemented methods which were used by Buder are FSC, TSS, FAC, WF, TAP and BOLD. All these methods were implemented into libgomp by extending the existing code and using the environment variable `OMP_SCHEDULE` for selecting a technique whenever the OpenMP schedule clause `schedule(runtime)` is used. To assess the implemented techniques, four benchmark suites, Rodinia [9], OmpSCR [10], NAS [11] and SPEComp [12] were used and, when necessary, modified to obtain profiling information of loop iteration times for the mean μ and standard deviation σ input values which are required in some of the techniques. The results show that no single method fits best for every application but rather, depending on the chosen benchmark, one is superior to the others. This is the evidence that OpenMP must include more loop scheduling techniques to cover much more types of applications with respect to performance. In this thesis, not only the methods used by Buder but also other, especially adaptive, techniques are implemented into the LLVM OpenMP runtime library.

Another close work to this thesis is recently done at TU Dresden [33] which presents a generic methodology for implementing additional scheduling techniques to an OpenMP runtime. They demonstrated the proposed methodology by implementing FAC to LLVM's libomp and presented first results with four scientific applications.

In the context of load balancing strategies, Penna et al. introduced a new design methodol-

ogy, including a simulator for assessing loop scheduling strategies, which helps to guide the study of new workload-aware loop scheduling techniques [34]. In contrast to other strategies, workload-aware scheduling methods try to achieve better load balance by taking the input workload into account and evenly distribute it among the threads. To validate their methodology, they proposed a new strategy as a proof of concept called *Smart Round-Robin* (SRR) [35] and implemented it in libgomp. This new method considers the input workload (i.e., the length of each iteration) in order to achieve near-optimal load balance. Since this technique depends on the iteration lengths, it requires some sort of profiling and preprocessing prior to the actual scheduling. A second novel workload-aware strategy was implemented in libgomp, called BinLPT [36]. One difference between SRR and this new strategy is that BinLPT schedules chunks of iterations instead of single ones. The results of both techniques have shown that they outperform OpenMP's `static` and `dynamic` scheduling strategies in irregular applications. Their approach of evenly distributing workload differs from all the techniques described in this thesis especially in how profiling is done. SRR and BinLPT both depend on precise workload information obtained beforehand to be able to evenly assign the workload across the threads. Techniques used in this thesis either use only mean and standard deviation inputs or obtain load information during runtime. Another difference is that SRR and BinLPT preprocess an optimal map for the iteration/thread assignment based on workload data which is a static scheduling description.
Similar work is done by Mottet L. who ported the same SRR technique from Penna et al. into Intel's OpenMP runtime [37]. He found similar results where SRR is 15% better than OpenMP's `dynamic` scheduling in some conditions. Furthermore, this work is of high relevance to this thesis since Intel's runtime is the same as LLVM's.
When dealing with NUMA[2] multicore machines, it is crucial to distribute work and its associated data in a way which exploits data locality to maximize performance. OpenMP's `dynamic` strategy is the first choice when scheduling irregular loops, however, it does not respect memory locality in NUMA machines. Durand et al. proposed a new scheduling technique called `adaptive` with the goal to provide a better dynamic scheduling technique for NUMA machines and irregular loops, while respecting data locality [38]. This new technique starts a static initial distribution of the iteration space, scheduling $\frac{N}{P}$ iterations for each thread. Load balancing is then done via work-stealing where idling threads steal half of the remaining iterations of another thread. On top of that, they extended `adaptive` with new OpenMP APIs to deal with the mentioned data locality. Their new strategy outperformed OpenMP's techniques on memory-bound and irregular loops, while providing similar performance to `static` on regular loads. In contrast to the work of Durand et al., this thesis does not focus on NUMA machines.
A different approach can be found in [39], [40] and [41], which proposed an automatic technique without having the user to choose a specific strategy. Their methods either automatically select an appropriate known loop scheduling technique for a given loop or derive a strategy based on online-profiling, loop analysis and system state. For instance, Zhang et al. [39] presented a hierarchical adaptive OpenMP loop scheduling technique for hyper-threaded

[2] Non-Uniform Memory Access

SMP[3] systems. This strategy samples different known techniques on a loop in its first several runs and then adapts by selecting a more appropriate technique on the remaining runs of the same loop. This is only applicable on loops which have multiple complete executions. Additionally, it decides based on the first few runs whether to use hyper-threading or not. Their approaches payed off especially in loaded systems, where unpredictable behavior is the case. This thesis does not implement any hierarchical or automatic, selection-based techniques, instead, it focuses on implementing and testing every particular strategy separately.
The last related work, that is discussed in this chapter is done by Kale V., who recently proposed a new addition to the OpenMP standard for adding user-defined scheduling techniques to OpenMP [42]. With this, the user can choose his custom strategy in code in a standardized way with the use of an extended `schedule()` clause. The user is hereby required to provide and link a custom library that implements the needed functions for the scheduling task.

[3] symmetric multiprocessing

4 Loop Scheduling in LLVM

This chapter explains how loop scheduling works in LLVM's libomp and mentions the requirements to implement new techniques. It also describes the methodology of how we have extended libomp. Exploiting parallelism on hardware with an increasing number of processing units requires complex techniques to schedule the tasks across the cores in an optimal way. Algorithms that contain parallel loops, which are responsible for most of their execution time, can use the full potential of the underlying system to improve the overall performance. Among different possibilities of realizing parallelism for loops on shared memory systems, OpenMP has proved itself as the de facto standard for parallelism. LLVM, with its Clang compiler and OpenMP runtime library, also called libomp, implements this standard to be used for parallelism. A general overview of LLVM is given in 2.3.2 in Chapter 2. The current state of libomp, from LLVM 8.0, provides four different loop scheduling techniques, `static`, `dynamic`, `guided` and `trapezoidal`. Many more techniques exist but they are not implemented in LLVM. However, the structure and design of libomp makes it possible to add new techniques by editing and extending a few files. To understand the requirements of such an extension, section 4.1 describes the design and workflow of loop scheduling in libomp.

4.1 Scheduling Overview in libomp

Libomp uses three functions to schedule iterations of a parallelized loop to processing units. Figure 4.1 shows the main parts of the scheduling process. Once an application is compiled with the use of a compiler like Clang, ICC or GCC, and thereafter linked to libomp by using the compiler flag `-fopenmp`, every loop that is parallelized with the compiler directive `omp parallel for` including the use of the scheduling clause `schedule(runtime)` is then scheduled by libomp. The library consists of many source files but since this thesis is focusing on the loop scheduling implementation only, six files suffice to be further discussed. These are *kmp.h, kmp_settings.cpp, kmp_runtime.cpp, kmp_global.cpp, kmp_dispatch.h* and *kmp_dispatch.cpp*. The three main functions responsible for the actual scheduling are inside of *kmp_dispatch.cpp* as depicted in Figure 4.1. Before the call of any of those mentioned functions, libomp first prepares a few things. The file *kmp.h* is the runtime header

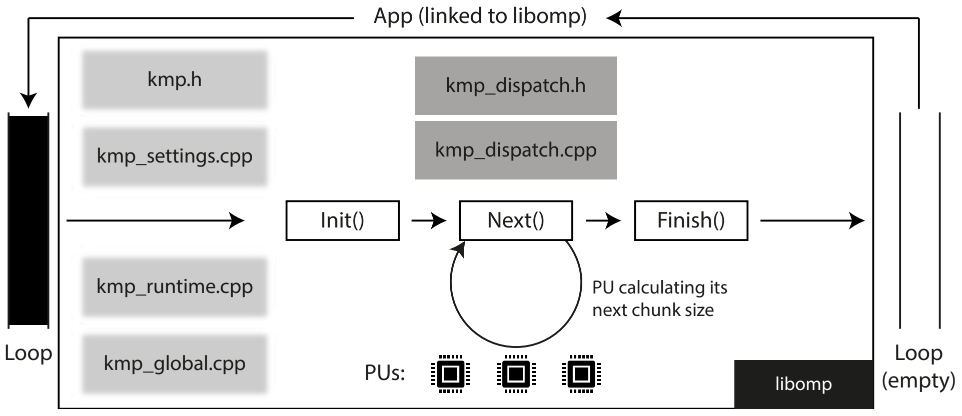


Figure 4.1: Loop scheduling in libomp. The source file *kmp_dispatch.cpp* contains the actual scheduling algorithms. Other files, such as *kmp.h* and *kmp_settings.cpp* do not implement the strategies but are required for selecting and recognizing them, including the initialization of environment variables.

file and declares many functions, data structures as well as variables which are used in the whole library. The environment variables are initialized in *kmp_settings.cpp*. The file *kmp_runtime.cpp* implements many functions for the runtime library. It does not play a main role for the scheduling part but helps to choose the selected scheduling technique out of the environment variable and this is why it is mentioned as well. Global variables, including the ones read from the environment variables, are initialized in *kmp_global.cpp*. Once everything is initialized and ready for the scheduling itself, for each thread, the compiler makes a call to the `init()` function inside *kmp_dispatch.cpp* whenever a pragma `omp parallel for` with the clause `schedule(runtime)` is encountered inside the application. This function then initializes the scheduling technique for the encountered parallel loop, such as pre-computation of constants or other needed preparations. The function `next()` is called by each thread thereafter, when the calling thread has finished the initialization part. This function implements the algorithm for the scheduling techniques. It means that the calling thread calculates its next chunk size with the selected technique. After it has obtained the size of that chunk, it processes it and then calls *next()* once again until the whole loop has been computed. Every thread does the same process by calling *init()* first and then repeatedly *next()* until there are no more iterations left to process. If this is the case then the threads call *finish()* to reset variables or free allocated memory. As every thread individually calls the functions and self-calculates its next chunk size, there is no need for a master thread, also known from centralized models. In order to extend the library with new scheduling techniques only a few files need to be edited, which is part of the next section.

4.2 Methodology on Extending libomp

One possible option to extend libomp is by searching the responsible code parts for the scheduling algorithms and then implementing new methods the same way as the existing techniques were implemented. This approach is effective but can produce some trouble if you don't know everything about the code. Luckily, the amount of source files

that need modifications is not high. Section 4.1 already described the relevant files for scheduling and these are exactly the files that require edits. A very recent case study [33] presented a generic methodology for extending an OpenMP runtime with new scheduling strategies. An example was given by implementing FAC into libomp. In this thesis, the methodology of implementing new strategies into libomp is based on the same approach as in the case study. The following description summarizes the methodology. First, the library must be able to select new strategies. For this, the enumeration `kmp_sched` listing all available scheduling techniques in header file *kmp.h* must be extended with a new item for each new strategy. In *kmp_runtime.cpp*, new case handling must be added for each new technique inside the function `__kmp_get_schedule`. Finally, the source file *kmp_settings.cpp* needs a modification to allow the user selecting new scheduling techniques by their names. The relevant functions here are `__kmp_parse_single_omp_schedule` and `__kmp_stg_print_omp_schedule` which must recognize the new strategies by their names.
The second part of extending libomp takes place in source file *kmp_dispatch.cpp.* This is the file to which the actual scheduling logic and algorithm belongs. Starting with the initialization of a scheduling technique, a new case for each new strategy must be added to function `__kmp_dispatch_init_algorithm`. This function is called once for each thread before the loop calculation begins. It focuses on initializing and preparing data structures, constants or even pre-computations of scheduling related information which are then needed later. Libomp already provides thread-private and shared data structures which can be extended in header file *kmp_dispatch.h.* Needed information can be stored in these data structures and read during the whole process of a single loop. The structures are called `dispatch_private_info_template` and `dispatch_shared_info_template`.
The third part also takes place in source file *kmp_dispatch.cpp* but this time inside the function `__kmp_dispatch_next_algorithm`. Once again, for each new scheduling technique, you must add a new case handler, that contains the actual scheduling algorithm to calculate the next chunk size. This function is also called by each thread, as soon as they have finished the initialization or computed a previous chunk and want to calculate their next chunk size for computation.
Finally, when there is no iteration left, the threads call `__kmp_dispatch_finish` or `__kmp_dispatch_finish_chunk` to cleanup. Scheduling related variables might need to be reset for the next loop.

Note: If there is need for additional environment variables that must be read and used in some scheduling strategies, additional modifications must take place. This can be done by declaring new variables in header file *kmp.h* and initializing them to a default value in file *kmp_global.cpp.* Lastly, the file *kmp_settings.cpp* must be modified to give libomp the ability to recognize, read and initialize the new environment variables. More precisely, the table `__kmp_stg_table[]` must be extended with a new entry for each new environment variable and an appropriate parser function. Chapter 5 gives more details about how each technique is implemented.

5 Implementation

This chapter describes how we have implemented the new DLS strategies which are presented in detail in Chapter 2. During implementation, the outlined methodology from Section 4.2 is followed. The newly implemented strategies have a common logic part that is described first in this chapter. Further deviations for a chosen technique are mentioned in the corresponding sections below. The main code for the strategies lies in source file *kmp_dispatch.cpp*, containing the two functions `init()` and `next()`, which are called by each thread separately, when a parallel loop has been encountered in the application. Generally, the structure of each technique's initialization and chunk size calculation is based on a common way. To initialize a scheduling technique, before the loop calculations starts, the function `init()` pre-computes variables or constants and stores them into thread-private or shared data structures to be used later. Algorithm 5 shows the common part of the

Algorithm 5 Initialization

```
1: procedure __KMP_DISPATCH_INIT
2:     switch schedule do
3:         case $factoring$
4:             preparations
5:             $private \leftarrow variables$
6:             $shared \leftarrow variables$
7:         case $bold$
8:             ...
9: end procedure
```

initialization. Depending on the technique's requirements, different preparations are made. The same thing applies to the function `next()`, which calculates the next chunk size for a calling thread. A general picture of how that code block looks like can be seen in Algorithm 6. A chosen scheduling case is executed to compute the chunk size and, in the end, set the loop boundaries for that new chunk to be processed. Mostly, a while loop is used in which the chunk size is calculated and, if the current starting point is not already taken by another thread, the while loop ends successfully and, if needed, updated variables are stored back to thread-private or shared data structures. After a thread has obtained its next chunk size, it processes that chunk with the calculated loop boundaries and calls the function `next()`

again until the loop is done.

Algorithm 6 Next chunk

```
procedure __KMP_DISPATCH_NEXT_ALGORITHM
    switch $schedule$ do
        case $factoring$
            while 1 do
                $init \leftarrow shared$                    ▷ read current start iteration
                $cs \leftarrow$ calculate chunk size
                $limit \leftarrow init + cs$                ▷ next starting point
                if obtain chunk == successful then
                    $shared \leftarrow limit$               ▷ update shared start iteration
                    break
                end if
                $private \leftarrow variables$
                $shared \leftarrow variables$
            end while
            set loop boundaries for current chunk to process
        case $bold$
            ...
end procedure
```

Some of the implemented techniques require additional environment variables to give the user the ability to set input values, which can be used in the appropriate strategy. Section 5.1 lists all implemented environment variables.

5.1 Environment Variables

While most of the newly implemented techniques don't require user-provided input values, some of them do. The ones which require them are FSC, TAP, FAC, WF and BOLD. Other strategies may have optional input values, such as static, dynamic or guided. Section 2.2 from Chapter 2 has detailed descriptions of the input values and their meaning. Table 5.1 summarizes all implemented environment variables and to which technique they belong. The environment variables were implemented in source file *kmp_settings.cpp*, following the methodology described in Section 4.2.

Table 5.1: New environment variables.

Variable	Values	Description
OMP_SCHEDULE	fsc, tap, fac, faca, fac2, fac2a, wf, bold, awf_b, awf_c, awf_d, awf_e, af, af_a	Selection of new scheduling techniques.
KMP_MU	Integer (>= 0)	Mean iteration execution time in microseconds. Required in TAP, FAC, FACa and BOLD.
KMP_SIGMA	Double (>= 0)	Standard deviation of iteration execution times in microseconds. Required in FSC, TAP, FAC, FACa and BOLD.
KMP_OVERHEAD	Integer (>= 0)	Scheduling overhead in microseconds. Required in FSC and BOLD.
KMP_ALPHA	Double (>= 0). Defaults to 1.	Scaling factor of the *coefficient of variation* (c.o.v.). Required in TAP.
KMP_WEIGHTS	Comma separated string with PU weights as doubles (> 0). Defaults to 1 for each PU. The sum of weights must be equal to the number of PUs. Example with 4 PUs: "0.9,0.9,1.1,1.1".	Indicates the weight for each PU. Required in WF.
KMP_DIVIDER	Integer (> 0). Defaults to 10.	To specify the number of subchunks. Optional in AF and AFa.
KMP_CPU_SPEED	Integer (> 0). Defaults to 2400.	To specify the CPU's reference clock frequency in megahertz (MHz). This is needed for the adaptive techniques BOLD, AWF and AF.
KMP_MIN	Integer (> 0).	To set a lower limit for the chunk size. This is optional and can be used for every strategy implemented in this thesis.

5.2 Fixed Size Chunking

This technique can be implemented simply by using FSC's chunk size formula from Section 2.2.2.2 during initialization and then dynamically scheduling chunks of that previously calculated size in the `next()` function. The formula requires profiling information which are read from environment variables `KMP_SIGMA` and `KMP_OVERHEAD`. The while loop in Algorithm 6 is not even needed here. One single atomic operation suffices to increase the shared chunk index whenever a PU acquires a new chunk.

5.3 Factoring

Factoring can be implemented in different ways. This thesis implements it in four versions, namely, FAC, FACa, FAC2 and FAC2a. The original version of Factoring, as described in Chapter 2, Section 2.2.2.5, is represented by FAC. FAC relies on strong synchronization between the threads. FACa does the exact same thing as FAC and produces the same chunks but avoids synchronization by involving more computation. In other words, FAC lets the first thread compute the chunk size for a given batch number, and every following thread, that wants its next chunk size from the same batch number, can simply read and re-use the already computed chunk size without computing it again. This means that for each batch, the chunk size is calculated only once and then shared among all threads. To implement this, the whole scheduling and chunk size calculation in function `next()` must be synchronized with the use of a mutex. No more than one single thread is allowed to calculate the next chunk size at the same time. Consequently, a while loop is not needed in FAC. A shared queue counter is used which holds the number of remaining chunks of the current batch. Whenever a thread wants to acquire a new chunk but the queue is empty, it calculates the chunk size for the new batch and stores it into the shared data structure.
FACa on the other hand uses a shared counter so that the threads can identify what the current batch number $j = \frac{counter}{P}$ is. There is no need to synchronize the scheduling part, instead, the threads atomically increment the shared counter at the beginning of function `next()` and calculate their next chunk size themselves by using the batch number and the factoring formula. This involves more computation since every thread calculates its next chunk size for a given batch number redundantly. Which one is the better choice depends on the system. If synchronization costs are higher than the costs caused by more computation, the user should choose FACa.

The other two implementations, FAC2 and FAC2a, don't use any profiling information. As with FACa, a shared counter is used to identify the current batch number. However, the chunk size formula is much simpler and less computationally intensive since the variable x is set to 2. FAC2 and FAC2a produce the exact same chunks but they defer in the way how they calculate the chunk size for a given batch number j. FAC2 uses the formula $Cs = \lceil \frac{1}{2}^{j+1} * \frac{N}{P} \rceil$. FAC2a uses a loop as in FACa to calculate the chunk size for the current batch number. The reasoning to provide this is to reduce redundancy and only apply the factoring formula to the last known batch's chunk size. By storing the last known, thread-private chunk size you can reduce the amount of calculations.

5.4 Weighted Factoring

The strategy WF uses the exact same algorithm as FAC2a from Section 5.3 but with the addition of weights. These are read from the environment variable `KMP_WEIGHTS` and the resulting FAC2a chunk sizes are multiplied with the PU's weight.

5.5 Taper

Taper is the only technique that requires a scaling factor α, read from the environment variable `KMP_ALPHA`. This factor is needed, in addition to μ and σ, to pre-compute the variable v_α during initialization. In the function `next()` the TAP formula 2.9, shown in Chapter 2, is used to calculate the chunk size. The number of remaining iterations is hereby calculated by the number of total iterations minus the current start iteration `init` obtained from the shared data structure.

5.6 The Bold Strategy

This technique is the first adaptive strategy implemented in this thesis. It makes use of many variables that are initialized first in function `init()` and then continuously updated in `next()` to adapt to current system and loop iteration states. BOLD also requires profiling information, i.e., `KMP_MU`, `KMP_SIGMA` and `KMP_OVERHEAD`. These three user inputs are needed during initialization as shown in Algorithm 2. After initializing all these variables, they must be stored in either thread-private or shared data structures. The variables `boldM`, `boldN`, `totalspeed` and `bold_time` are shared, all other remain private.
In function `next()`, Algorithm 3 is used to calculate the next chunk size of a PU. However, an updated variable `boldN` must be used in the mentioned algorithm. To maintain the shared variable `boldN`, you need timing information. For this, the implementation stores three time points t_1, t and t_2, also depicted in Figure 2.5. The time t_2 is initialized to the current time at the beginning of function `next()`. Immediately, also at the beginning, the time point t is read from a shared variable `bold_time` which then itself is updated to the current time like t_2. `bold_time` can then be used by every other thread, to initialize t. The remaining time point t_1 is nothing else than the old t_2 of that same PU. This is done by storing t_2 in thread-private data to be used in the next chunk. With all these information, the next chunk size can be calculated according to BOLD's algorithm from Chapter 2.

5.7 Adaptive Weighted Factoring Variants

All AWF variants are based on WF's implementation. The difference is that AWF adapts the weights before being applied to factoring. AWF-B uses batches as in FAC. The first batch size is calculated during initialization in `init()` by taking $\frac{1}{2} \times N$ as the initial batch size and $\frac{1}{2} \times \frac{N}{P}$ as its chunk size. The weights are initially set to 1 for the first chunk. AWF-B uses a shared vector of size P to hold each PU's current π, also called the weighted average ratio. This vector is initialized to all zeros, meaning, no PU has yet finished any chunk and updated its π.
In function `next()`, after the very first chunk has been computed with an initial weight of 1, AWF-B first calculates the weight of a PU and then continues like WF. The weight calculation happens before the while loop. The procedure and formulae to update the weight are described in Section 2.2.2.10 of Chapter 2. The implementation includes shared locks (from C++14) to protect individual elements of the shared vector from corruptness. To measure the time of individual chunk execution times, a time point is stored at the

beginning of function `next()` and at the end of it. The time difference between the end of a previous scheduling task and the beginning of a succeeding one is taken as the chunk execution time.
AWF-C is very similar to AWF-B but it is not batched. Instead, each chunk size is calculated by applying the factoring rule to the remaining iterations. The remaining variants AWF-D and AWF-E have the exact same implementations as AWF-C and AWF-B but the only difference here lies in the time measurement, that not only measures the chunk execution time but also includes the scheduling time itself. For this, a single time point is stored at the beginning of each scheduling task and the time difference between the last stored point and the new one is taken for the formula to adapt the weight.

5.8 Adaptive Factoring

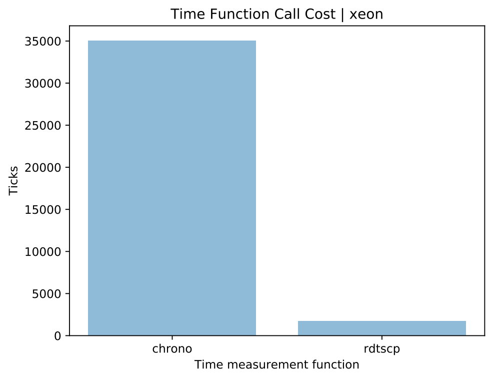
This technique is the last adaptive one implemented in this thesis. Algorithm 4 shows the steps of how the chunk sizes are calculated. However, the implementation defers slightly from the description in Section 2.2.2.12 because of performance reasons. Instead of measuring every individual iteration's execution time and adapting to every each of them, the implementation schedules portions of a calculated chunk size (i.e. sub-chunks) of iterations and records their average finishing times. In other words, one sub-chunk gives one average iteration finishing time. This information is then used to calculate the mean and standard deviation of the whole chunk, once all of its sub-chunks are finished. After a whole chunk has been computed, a new chunk is calculated using AF's formulae and the new estimations from previous chunks. The new chunk is again divided into sub-chunks and the process is repeated. The size of a sub-chunk relies on the number of sub-chunks you want. Per default, a chunk is divided by 4 and, thus, resulting in four sub-chunks. To give the user more flexibility, the divider can be set in environment variable `KMP_DIVIDER`. Furthermore, two shared vectors of size P are used to store the current mean and standard deviation values of each PU. As in AWF, the access to the shared vectors are protected by shared locks.
AF_a uses the exact same implementation as AF but with the difference that it not only takes the chunk execution times into account but the total time including scheduling.

6 Optimizations

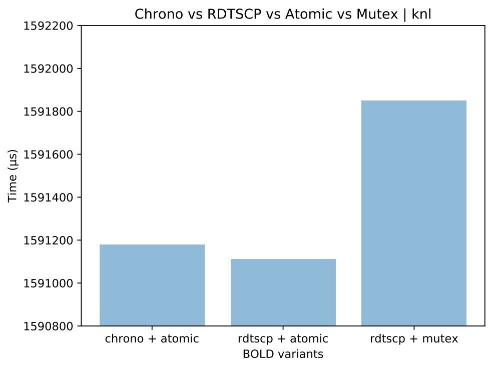
This chapter holds explanations and performance tests of a few optimizations made to the implementation. More precisely, the choice of time measurement functions, atomic versus mutex implementations and different factoring variants are discussed.

The first choice was to find the most efficient way to measure execution times or global time points. There is the chrono library from C++ standard [43] and the hardware instruction RDTSCP [44], that returns the Time Stamp Counter (TSC) from the CPU. Figure 6.1(a) compares these two methods to obtain the current time point. The number of CPU cycles (or ticks) needed is way higher when using the chrono library than calling the function rdtscp(). Both calls require less than a millisecond but if a scheduling technique makes use of many time function calls, this can come costly. This was the reason why we used rdtscp() in every scheduling technique for time measurements. Figure 6.1(b) shows the two time function in action while using BOLD strategy with the EPCC schedbench benchmark [8]. This test is an average of 20 repetitions and there is a measurable difference between chrono and rdtscp(). The difference is even higher when comparing an implementation of BOLD using atomic accesses (i.e. hardware instructions) or doing the same with mutexes. This is the reason, why the implementation of every scheduling strategy makes use of atomic instructions instead of mutexes. However, in some techniques, such as FAC, the use of mutual exclusion is inescapable.

The reasoning of four different factoring implementations (FAC, FACa, FAC2, FAC2a), as presented in Section 5.3, is to find the fastest and most efficient one. FAC and FAC2 are the original implementations based on the description of factoring in Chapter 2. FACa tries to improve performance of FAC by avoiding mutual exclusion and, instead, using atomic operations. FAC2 uses the factoring formula to compute the chunk sizes while FAC2a uses an improved loop for the same formula. Figure 6.2 compares all four factoring implementations, using the EPCC schedbench benchmark. While FAC is the slowest, FAC2 and FAC2a are around 1.453 % faster than FAC. The mutex-free variant FACa is also faster than FAC.



(a) One chrono call takes around 14.6 μs compared to 0.73 μs of a call to rdtscp(). Rdtscp() is around 20 times faster.



(b) Atomic vs mutex versions of BOLD.

Figure 6.1: Performance results of two different time measurement options on an Intel Xeon CPU E5-2640 v4 (a) and EPCC schedbench execution times with atomic and mutex implementations of BOLD on an Intel KNL CPU with 60 threads (b).

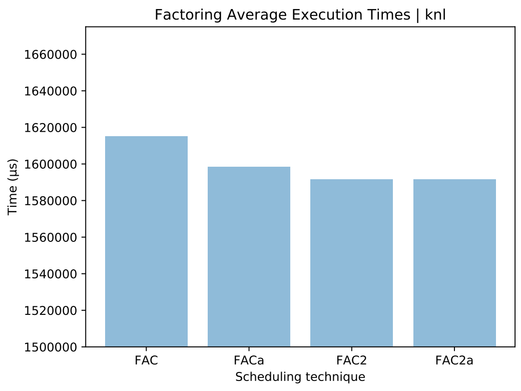


Figure 6.2: EPCC schedbench, tested on an Intel KNL CPU with 64 threads and 20 repetitions. Loop size is 6.4 million iterations.

7 Validation

The implemented strategies from Chapter 5 must undergo a validation process to verify the correctness of chunk size calculation. This can be done in different ways, such as comparing the chunks with another, already verified implementation or a standalone tool that only calculates the chunk sizes based on the proposed formulae. However, since the most reliable source of a strategy is the original paper itself, we compare the produced chunks with the expected ones that we calculate based on instructions from the according paper. The following sections give more details on how the validation process works for nonadaptive and adaptive strategies.

7.1 Nonadaptive Techniques

Nonadaptive techniques are simpler to validate because the chunk sizes are calculated based on formulae with fixed information and no adaptation to system state or other side effects which could change the calculation. By printing out the scheduled chunk sizes and comparing these with the expected chunks based on the paper, you can verify that the strategy itself is correct. An example can be given for FAC2 below. It shows the expected and experimented chunks when using a loop with 128 iterations and 4 threads. The expected chunks are calculated with the FAC2 formula from 2.2.2.5. The experimented results can have different orders of chunks due to PUs being slower or faster and the chunks being scheduled dynamically. However, the chunks should appear with the same size and amount as in the expected case and the total number of iterations must be the same.

```
# Iterations in this loop: 128
# Threads: 4

Expected chunk sizes (formula 2.7):
Each batch has P = 4 chunks of the same size calculated by R/(2*P)
    ↪ .
The rule is, that there are P chunks of the same size,
and each batch' size is divided by 2.

```

```
-------------- Expected ---------------

Something similar to the following should happen:
                   [B 1] [B 2] .........[B 6]
Thread 0: My chunks were: [16] [8] [4] [2] [1] [1] . Sum = 32.
Thread 1: My chunks were: [16] [8] [4] [2] [1] [1] . Sum = 32.
Thread 2: My chunks were: [16] [8] [4] [2] [1] [1] . Sum = 32.
Thread 3: My chunks were: [16] [8] [4] [2] [1] [1] . Sum = 32.

------------ Experimented ------------

Thread 3: My chunks were: [16] [8] [4] [2] [1] [1] . Sum = 32.
Thread 2: My chunks were: [16] [8] [4] [2] [2] [1] . Sum = 33.
Thread 0: My chunks were: [16] [8] [4] [1] [1] [1] . Sum = 31.
Thread 1: My chunks were: [16] [8] [4] [2] [1] [1] . Sum = 32.
```

7.2 Adaptive Techniques

As with nonadaptive techniques, the adaptive ones are validated similarly but the process is more complex. The chunk sizes are not only calculated with fixed formulae and constants but a few variables can change during runtime. To overcome this issue, we decided to print out every state information during runtime, i.e. the adapted variables and time measurements, and use this data to manually calculate the expected result, again, with the help of the paper itself. When the experimented chunks coincide with the expected result, the validation succeeds.

8 Experiments

Here, the results of this thesis are presented. Starting with the used system, a short discussion about scheduling overhead and compiler versus runtime performance tests, continuing with an overview of all the used benchmark applications, the design of experiments and, finally, concluding with benchmark suites and their results thereafter. The goal of this chapter is to show how the newly implemented techniques perform compared to the available scheduling strategies. Many different benchmarks are picked to give a broad view of application and loop characteristics. It is expected that with irregular loops and/or system variances, strategies with better load balancing outperform techniques like static or FSC. One more interesting thing is to see if there are strategies that can perform well in every application, or polarizing ones, that either perform the best in some benchmarks and the worst in others.

8.1 The System

For every test and benchmark run, the miniHPC cluster of the University of Basel was used. It consists of 22 dual socket Intel Xeon CPUs and 4 Intel Xeon Phi *Knights Landing* (KNL) CPUs. The detailed specifications can be seen in Table 8.1.

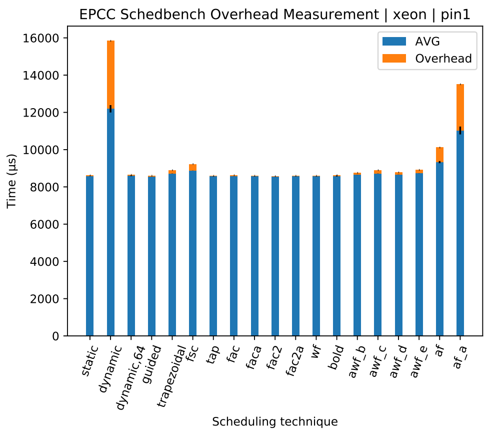
Table 8.1: System specifications of miniHPC cluster.

	Intel® Xeon® Processor E5-2640 v4 [45]	Intel® Xeon Phi^{TM} Processor 7210 [46]
Node count	22 (44 CPUs)	4
CPU speed (GHz)	2.4	1.3
Cores / CPU	10	64
Threads / CPU	20	256
RAM (GB)	64	128
Cache (MB)	L3: 25	L2: 32

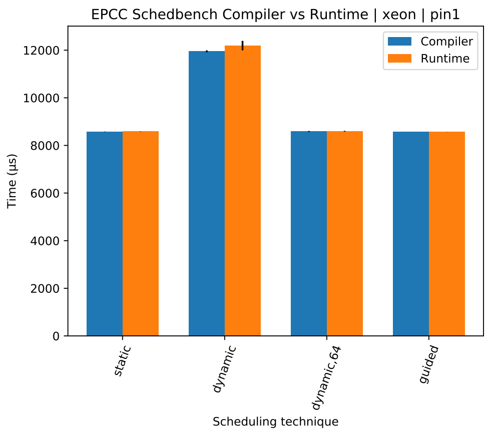
All C/C++/Fortran applications and libomp are compiled with Intel Compiler 19.0.

8.2 Scheduling Overhead and Compiler vs Runtime

Each strategy has its own scheduling overhead depending on the complexity of the used algorithm. To gain more insight in scheduling overhead of the implemented strategies, one can use the EPCC schedbench application [8] which measures the overhead of a parallel run compared to a reference run without parallel execution, thus, no loop scheduling at all. Figure 8.1(a) depicts the measured execution times of all scheduling techniques where the orange bar illustrates the overhead compared to a reference serial execution. As expected, dynamic (or SS) with chunk size 1 produces the most scheduling overhead. AF does produce the seconds most overhead while all other remain similar.



(a) EPCC Scheduling overhead



(b) EPCC compiler vs runtime

Figure 8.1: EPCC schedbench results tested on Xeon node with 20 threads, 50 repetitions, 2000 microseconds test time and 1 microsecond delay time.

Figure 8.1(b) shows the difference of using the OpenMP parallel directive with `schedule(static|dynamic|guided)` and `schedule(runtime)`. The call to the runtime requires the environment variable to be read and could produce more overhead. However, the results show that no big changes are expected. In all the following experiments, the scheduling technique is always selected with the environment variable.

8.3 The Benchmarks

To assess all the implemented techniques, 5 different benchmark suites and a total of 24 applications were selected, analyzed, prepared and tested on the miniHPC cluster. The applications stem from various scientific domains, such as molecular dynamics, physics, n-body simulations, math and weather prediction. To have a better overview, all applications and relevant information can be seen in Table 8.3.

Table 8.3: The tested benchmark suites and applications.

Suite	App	Language	Domain	Used Parallelism	# of parallel loops with `schedule(runtime)`	# of runs
NAS 3.4	BT	Fortran	Math	OpenMP	3	30
	CG				1	
	FT				4	
	IS	C	Bucket Sort		2	
	LU	Fortran	Math		5	
	MG				1	
	SP				3	
	EP				1	
CORAL	Lulesh	C	Hydrodynamics		3	
CORAL2	Quicksilver	C++	Monte Carlo transport simulations	OpenMP, MPI + OpenMP (4 nodes)	1	
N/A	Sphynx	Fortran	Smoothed Particle Hydrodynamics (SPH)	MPI + OpenMP (4 nodes)	1	
	SPH-EXA	C++			2	
SPEC OMP 2012	350md	Fortran	Molecular Dynamics	OpenMP	9	
	351bwaves		Computational Fluid Dynamics		3	
	352nab	C	Molecular Modeling		5	
	360ilbdc	Fortran	Lattic Boltzmann		5	
	362fma3d		Mechanical Response Simulation		1	
	363swim		Weather Prediction		3	
Rodinia	lud	C	Linear Algebra		1	
	lavaMD		Molecular Dynamics		1	
OmpSCR	cmandel		Math		1	
	md		Molecular Dynamics		1	
N/A	MANDELBROT		Math		1	
	AC		Adjoint Convolution		1	

8.4 Design of Experiments

All applications were tested on the miniHPC cluster with 30 repetitions. Multithreading was always deactivated. For every Xeon test, 20 threads were used and 64 threads for KNL respectively. To prepare the applications to be tested, they were first traced with a tool called Score-P [47]. With these traces and the help of a visualization tool, Vampir, you can find the most time consuming parallel loops inside the application. It is crucial to use the DLS techniques only for the heaviest loops, otherwise, you will produce more overhead than accelerating the application. After having found the biggest loops, they were modified in the source files by using the clause `schedule(runtime)` to make sure our new implementations are called. Some of the strategies require profiling information which must be obtained prior to the tests. For this, we have implemented a special technique itself called *profiling* that schedules single iterations and measures their mean and standard deviation of execution times. This must be done for both CPU types (Xeon and KNL) separately. After all these preparations, the application can be tested. To guarantee that each repetition is performed on a clean and fresh node, a Slurm [48] job script was used that submitted each benchmark job separately to an available node. With 26 total apps (including hybrid versions and different input sizes for certain apps), 3 pinning strategies for Xeon and 1 for KNL, 19 scheduling techniques and 30 repetitions, a total of 44460 individual jobs were executed on Xeon nodes and 14820 on KNL.

8.4.1 Pinning Strategy

Most of the applications were tested with 3 different pinning strategies. OpenMP provides the environment variables `OMP_PROC_BIND` and `OMP_PLACES` which can be used to enable custom pinning strategies. Our first pinning strategy makes sure that the threads are not allowed to change cores and produces an equal thread-to-core alignment with 1 thread per core. Pinning 2 uses unequal and non-fixed binding. It binds the first half of threads (incremental thread id) to a set of the first 1/4 cores (double-loaded). The remaining half of threads is assigned to a set of the second half of cores (single-loaded). The binding within a set is not further defined and may change. Pinning 3 uses fixed thread-to-core binding like pinning 1 but with unequal balance like pinning 2. More precisely, a core can have 1 to 4 threads pinned to it. In this chapter, only results with pinning 1 and 3 are shown, the second pinning strategy can be seen in Appendix A. The idea of overloaded CPU cores is to analyze the weighted and adaptive techniques whether they can improve performance or not. Appropriate weights must be set in the environment variable `KMP_WEIGHTS` to be used in WF. If a core has two threads on it, the weight is set to 0.5, if there are four threads, the weight is 0.25, etc. Table 8.5 shows the details of each pinning strategy for Xeon tests and which weights are used. Table 8.7 does the same for KNL tests. As for Xeon, Figure 8.2 contains an illustration of all three pinning strategies.

Table 8.5: Pinning strategies for Xeon.

Env. Variable	Pin 1	Pin 2	Pin 3
	20 threads, 20 PUs	20 threads, 15 PUs	20 threads, 12 PUs
OMP_PROC_BIND	close	close	close
OMP_PLACES	cores	"{0:5:1},{10:10:1}"	"{0},{1},{1},{1},{1}, {2},{2},{3},{4}, {5},{5},{5}, {6},{7}, {7},{8},{9}, {10},{10},{11}"
KMP_WEIGHTS	"1,1,1,1,1,1,1,1,1,1, 1,1,1,1,1,1,1,1,1,1"	"0.5,0.5,0.5,0.5,0.5, 0.5,0.5,0.5,0.5,0.5, 1,1,1,1,1,1,1,1,1,1"	"1.0,0.25,0.25,0.25, 0.25,0.5,0.5,1.0,1.0, 0.33,0.33,0.33,1.0, 0.5,0.5,1.0,1.0,0.5, 0.5,1.0"

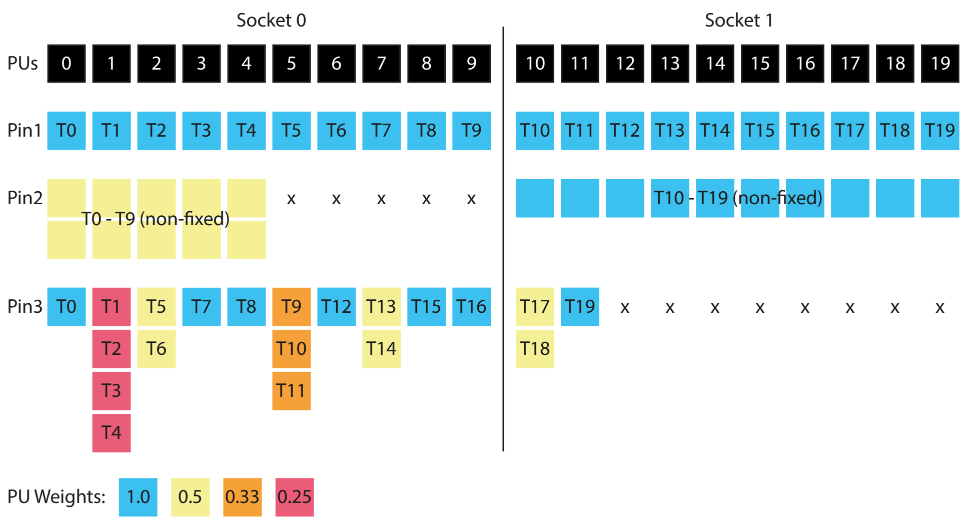


Figure 8.2: Illustration of the three pinning patterns for Xeon. An 'x' marks a PU as non-used. Pinning 2 defines two places of PUs with a set of threads for each place and there is no fixed thread-to-core binding within a place.

Table 8.7: Pinning strategies for KNL.

Env. Variable	Pin 1	Pin 2	Pin 3
	64 threads, 64 PUs	64 threads, 48 PUs	64 threads, 37 PUs
`OMP_PROC_BIND`	close	close	close
`OMP_PLACES`	cores	”{0:16:1},{32:32:1}”	”{0},{1},{1},{1},{1},{2},{2},{3},{4},{5},{5},{5},{6},{7},{7},{8},{9},{10},{10},{11},{12},{13},{13},{13},{13},{14},{14},{15},{16},{17},{17},{17},{18},{19},{19},{20},{21},{22},{22},{22},{22},{23},{23},{24},{25},{26},{26},{26},{27},{28},{28},{29},{30},{31},{31},{32},{33},{34},{34},{34},{34},{35},{35},{36}”
`KMP_WEIGHTS`	”1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1”	”0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1”	”1.0,0.25,0.25,0.25,0.25,0.5,0.5,1.0,1.0,0.33,0.33,0.33,1.0,0.5,0.5,1.0,1.0,0.5,0.5,1.0,1.0,0.25,0.25,0.25,0.25,0.5,0.5,1.0,1.0,0.33,0.33,0.33,1.0,0.5,0.5,1.0,1.0,0.25,0.25,0.25,0.25,0.5,0.5,1.0,1.0,0.33,0.33,0.33,1.0,0.5,0.5,1.0,1.0,0.5,0.5,1.0,1.0,0.25,0.25,0.25,0.25,0.5,0.5,1.0”

8.5 Profiling

Schedules like FSC, TAP, FAC and BOLD require profiling information prior to execution. Some of them are fixed across all benchmarks such as the scheduling overhead which is required for FSC and BOLD. `KMP_OVERHEAD` has been measured and set to 1 microsecond for FSC on both platforms, Xeon and KNL. For BOLD, it is set to 2 microseconds on Xeon and 7 on KNL. TAP's scaling factor α is set to 1 for all benchmarks and platforms. The variable `KMP_CPU_SPEED` is set to 2400 for Xeon and 1300 for KNL, to make sure that the correct CPU clock frequency is used with the time measurements. For every benchmark and scheduling technique (except static, dynamic, guided and trapezoidal), the minimum chunk size is set to 10 via the environment variable `KMP_MIN`.
The profiling information mean and standard deviation are measured precisely for every application and platform. Table 8.9 gives an overview of them. Since there are countless possibilities to find the right input value, it is difficult to compare scheduling techniques such as FSC, FAC or BOLD with others. The input can be crucial for their performance.

Table 8.9: The apps' profiling results consisting of mean iteration execution time and its standard deviation per app. These inputs were used in the experiments.

App	Xeon		KNL	
	Mean (μs)	SD (μs)	Mean (μs)	SD (μs)
NASOMP-BT	60	10	245	26
NASOMP-CG	1	0.6	3	1.5
NASOMP-FT	460	50	6100	670
NASOMP-IS (C)	270	250	800	630
NASOMP-IS (D)	12800	11800	162798	146080
NASOMP-LU	20	5	50	11
NASOMP-MG	7	6	12	6
NASOMP-SP	20	5	70	10
NASOMP-EP	1546	39	9961	106
CORAL-Lulesh	1	10	23	253
CORAL2-Quicksilver	3	2.6	16	11
CORAL2-Quicksilver (hybrid)	19	15	26	19
Sphynx	1150	265	3600	510
SPECOMP2012-350md	4300	1270	18170	8200
SPECOMP2012-351bwaves	1933	430	4516	245
SPECOMP2012-352nab	400	260	1000	730
SPECOMP2012-360ilbdc	1	3.7	2	1.2
SPECOMP2012-362fma3d	3	3.6	12	4
SPECOMP2012-363swim	320	130	600	60
RODINIAOMP-lud	3	2	5	1.7
RODINIAOMP-lavaMD	5047	451	18122	1572
OMPSCR-cmandel	109	180	424	701
OMPSCR-md	1490	355	5090	2430
MANDELBROT	7	3.6	58	42
Adjoint Convolution	252	146	1931	1183
Random Sleep	360	1063		
SPH-EXA	36	10	160	26

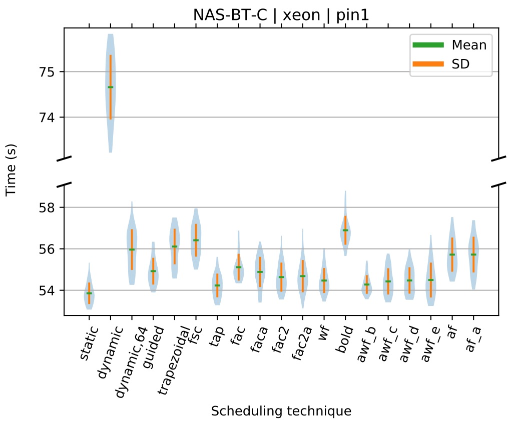
8.6 NAS Parallel Benchmarks

The first set of applications that are tested in this thesis come from the NAS Parallel Benchmarks 3.4 [11]. We have tested 8 applications out of this suite. The modifications and details are listed in Table 8.11.

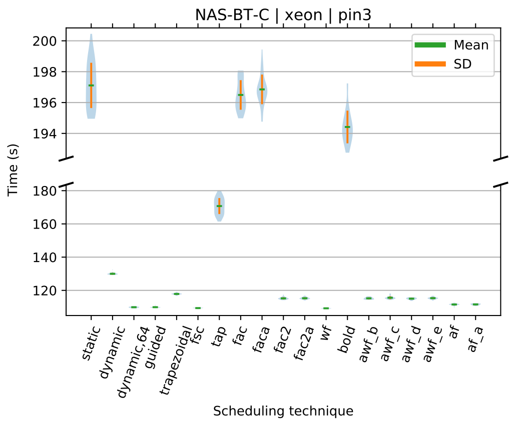
Table 8.11: NAS Parallel Benchmarks details.

App	Size	Modified loop file/line	Description
BT	C	x_solve.f/49, y_solve/49, z_solve/49	Solve a synthetic system of nonlinear PDEs using block tridiagonal kernel.
CG	C	cg.f/517	Estimate the smallest eigenvalue of a large sparse symmetric positive-definite matrix using the inverse iteration with the conjugate gradient method as a subroutine for solving systems of linear equations.
FT	C	ft.f/170, ft.f/205, ft.f/524, ft.f/570	Solve a three-dimensional partial differential equation (PDE) using the fast Fourier transform (FFT).
IS	C, D	is.c/544, is.c/707	Sort small integers using the bucket sort.
LU	C	ssor.f/103, ssor.f/135, rhs.f/63, rhs.f/189, rhs.f/345	Solve a synthetic system of nonlinear PDEs using symmetric successive over-relaxation (SSOR) solver kernel.
MG	C	mg.f/606	Approximate the solution to a three-dimensional discrete Poisson equation using the V-cycle multigrid method.
SP	C	x_solve.f/30, y_solve.f/30, z_solve.f/35	Solve a synthetic system of nonlinear PDEs using scalar pentadiagonal kernel.
EP	C	ep.f/166	Generate independent Gaussian random variates using the Marsaglia polar method.

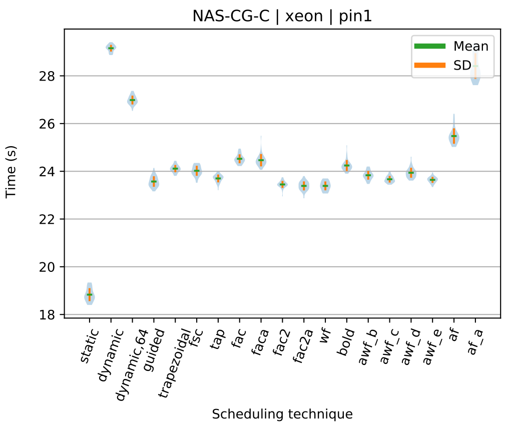
When looking at the results with pin1 strategy, the first clear thing is that depending on the application and loop characteristics, one technique can be good or bad. There is no superior strategy for every case. As an example, dynamic can perform worse than all others such as in Figure 8.3(a) but may also be the best in NAS IS as depicted in Figure 8.4(c). However, one can say that very load-balanced techniques such as dynamic or FAC2 and AWF variants perform better with irregular loops. The opposite is with regular loops which have almost no variance in iteration times, where static outperforms every other strategy. This behavior can be seen in NAS CG, depicted in 8.3(c), or MG in Figure 8.6(a). The variance of a loop, however, does not decide alone whether dynamic or static should be chosen. It also depends on the system, number of iterations, their mean execution time and data locality demands. Just by running the same applications CG and MG on the KNL platform with 64



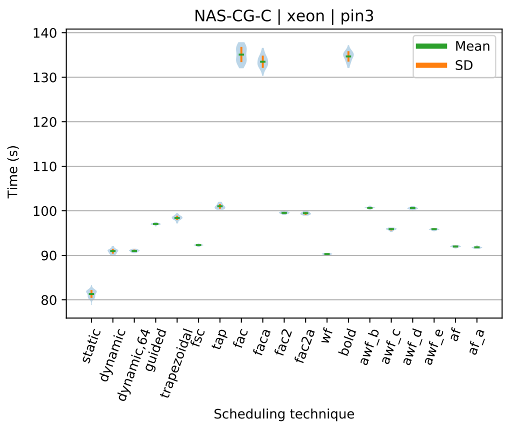
(a) Xeon Pin 1



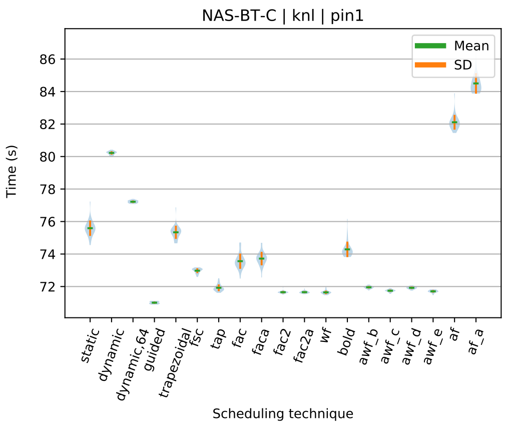
(b) Xeon Pin 3



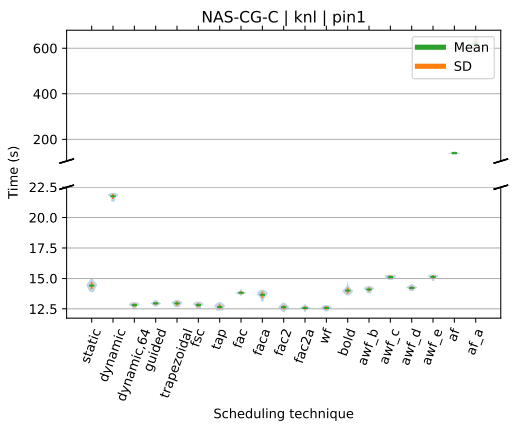
(c) Xeon Pin 1



(d) Xeon Pin 3



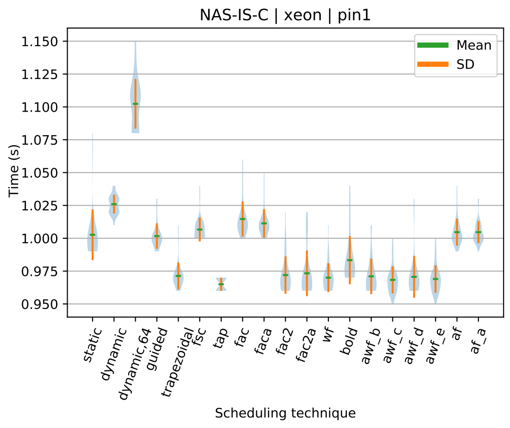
(e) KNL Pin 1



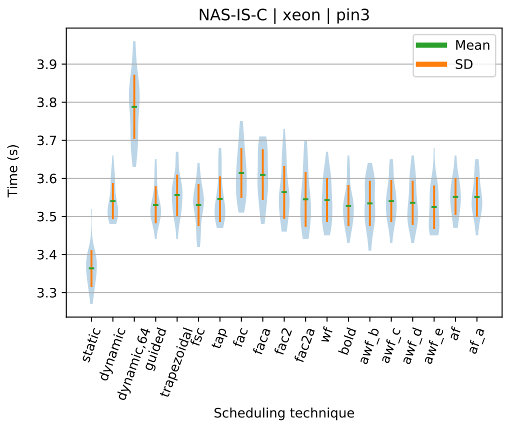
(f) KNL Pin 1

Figure 8.3: NAS BT and CG Class-C results.

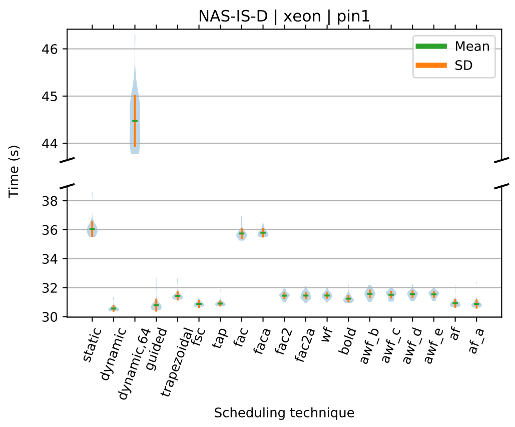
PUs instead of 20 (see Figures 8.3(f) and 8.6(e)), the performance of static falls behind and is no longer the best. In the case of MG on KNL, the techniques FSC and FAC2 improve the performance by 6.1 % compared to the fastest OpenMP strategy guided. This gives an idea of how different systems require advanced or better-fitting strategies.



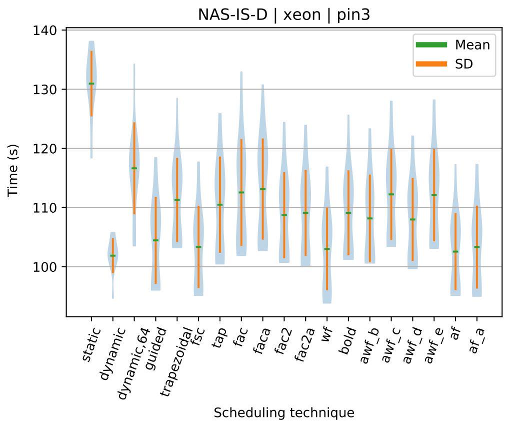
(a) Xeon Pin 1



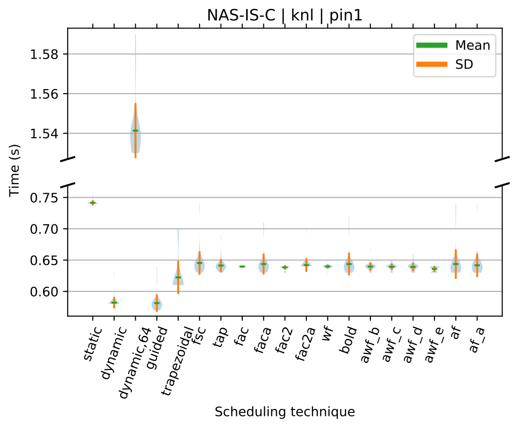
(b) Xeon Pin 3



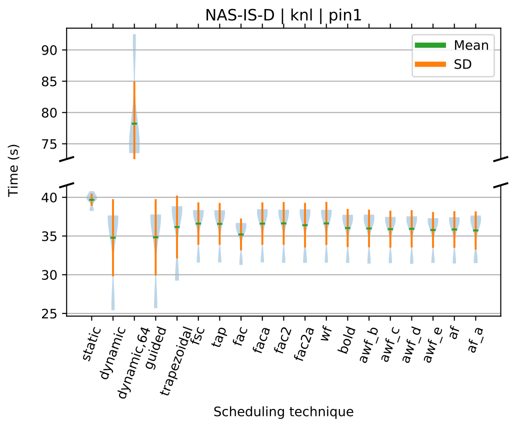
(c) Xeon Pin 1



(d) Xeon Pin 3



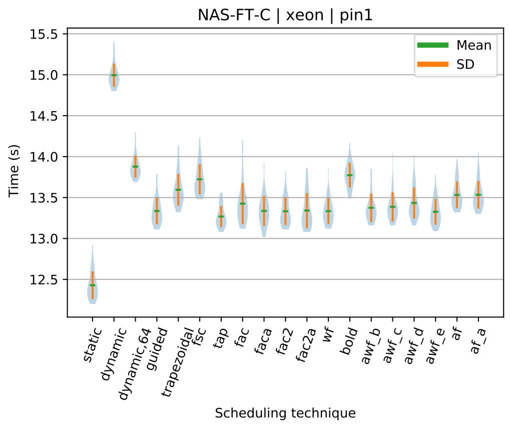
(e) KNL Pin 1



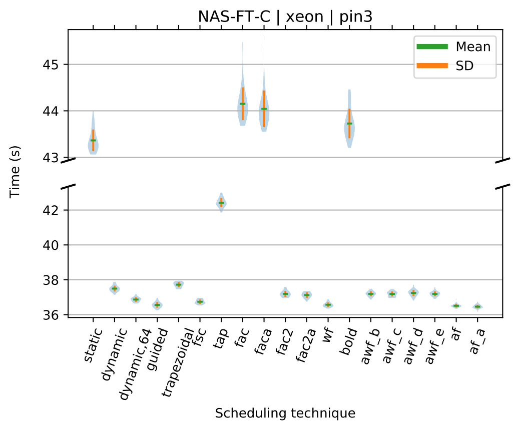
(f) KNL Pin 1

Figure 8.4: NAS IS Class-C and D results.

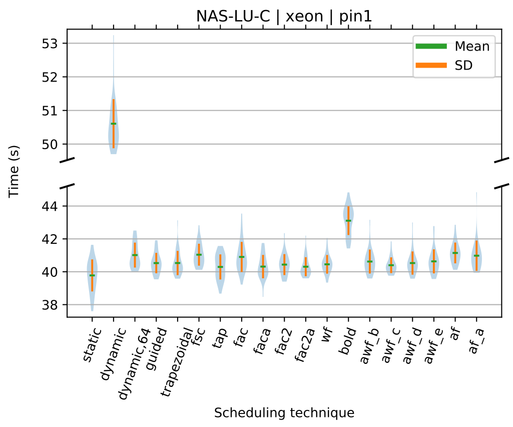
The picture is different when comparing pin3 strategy with pin1. Due to the cause of overloaded PUs with more than one thread, a PU can perform worse if it is assigned chunks from multiple threads simultaneously. The strategy static can lead to massive performance loss in this case since it distributes equal-sized chunks to all PUs. Figures 8.7(a) and 8.7(b)



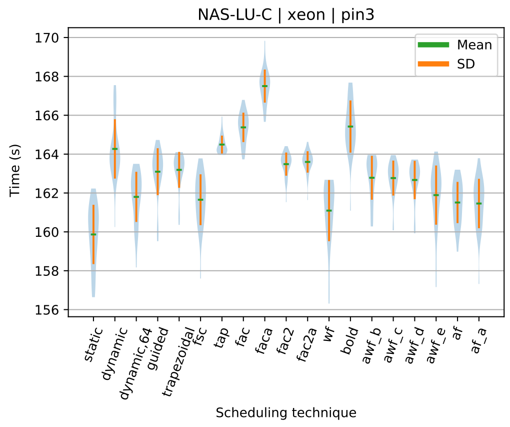
(a) Xeon Pin 1



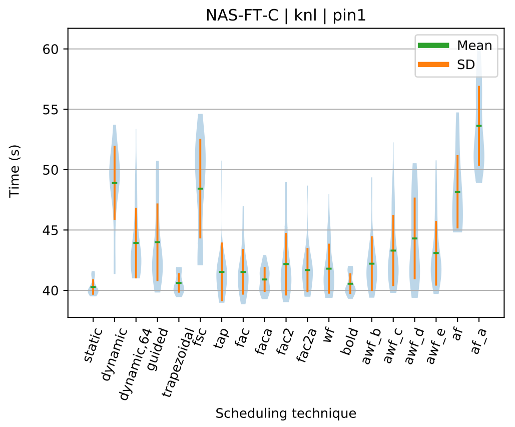
(b) Xeon Pin 3



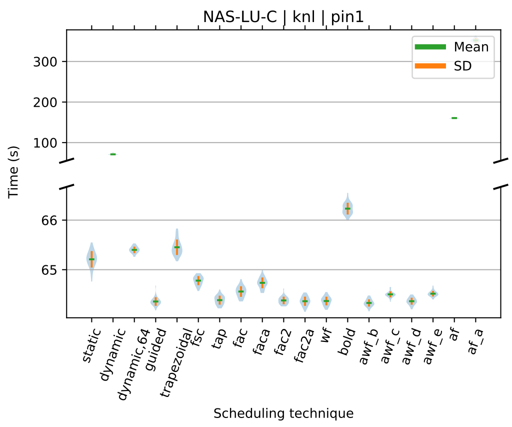
(c) Xeon Pin 1



(d) Xeon Pin 3



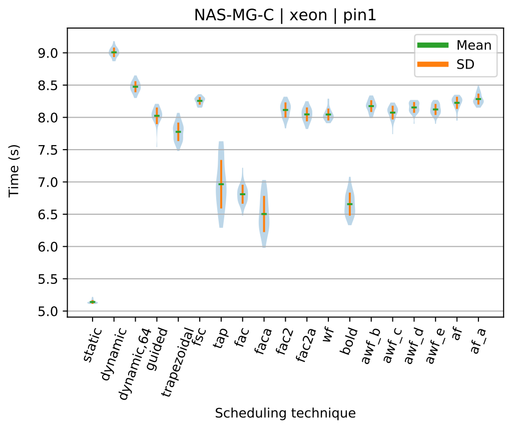
(e) KNL Pin 1



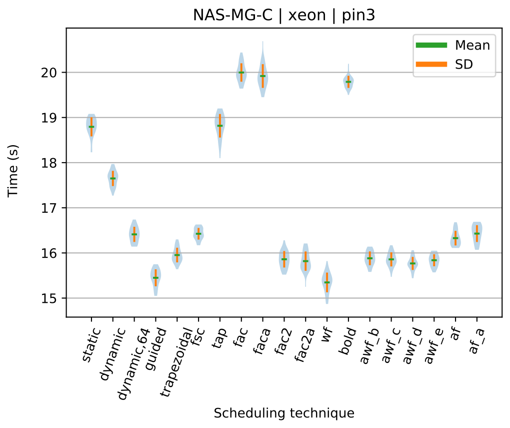
(f) KNL Pin 1

Figure 8.5: NAS FT and LU Class-C results.

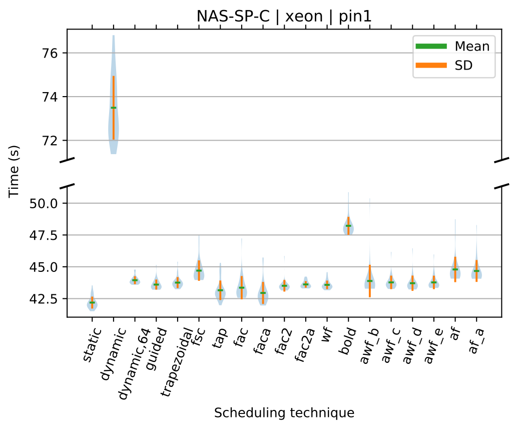
illustrate this phenomena very well, where static performs bad in combination with pin3 strategy. At the same time, WF can show an improvement of almost 20% compared to FAC2 and FAC2a, which are the same strategy but without the weights. Nearly in every



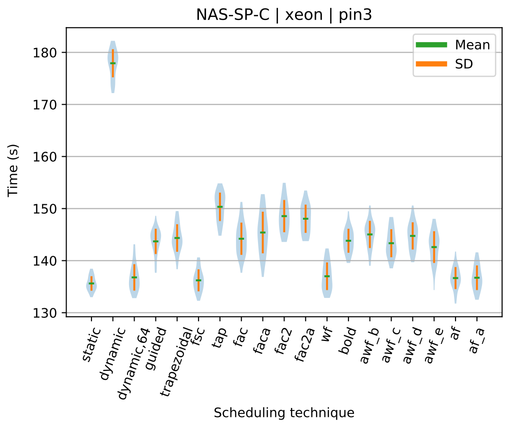
(a) Xeon Pin 1



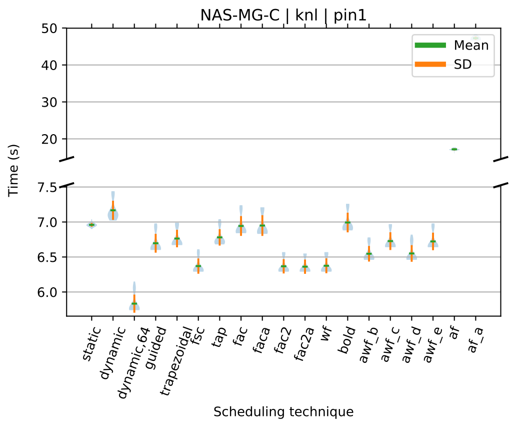
(b) Xeon Pin 3



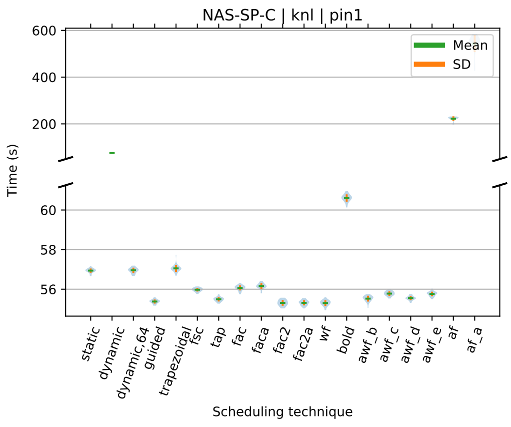
(c) Xeon Pin 1



(d) Xeon Pin 3



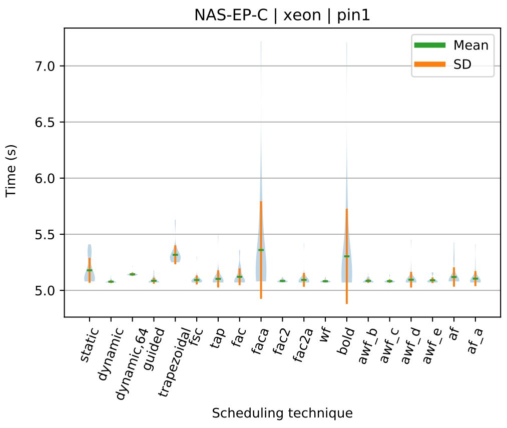
(e) KNL Pin 1



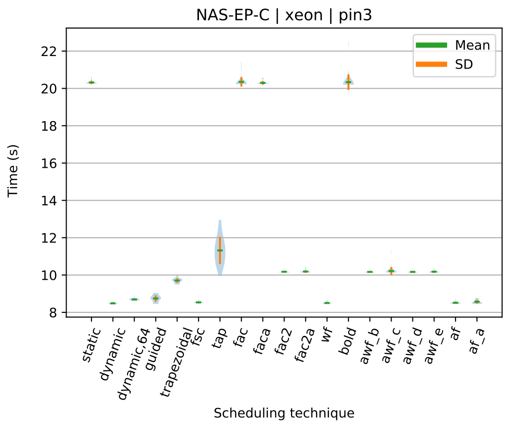
(f) KNL Pin 1

Figure 8.6: NAS MG and SP Class-C results.

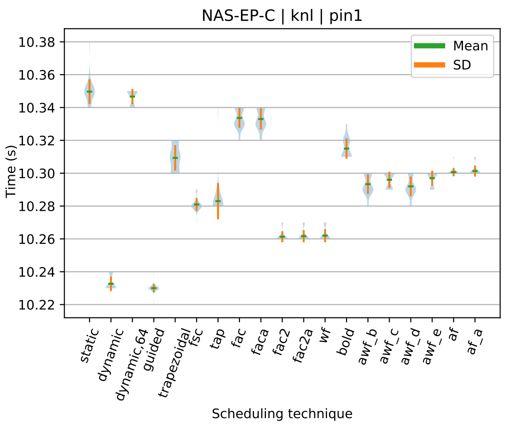
pin3 case, WF is faster than its FAC2 counterpart. This shows us, that weighted strategies can improve systemic load imbalance or heterogeneous PUs. Same accounts for the adaptive techniques AWF and AF which perform often better than static or dynamic, as depicted in 8.3(b) or 8.5(b). Pin3 strategy does not perfectly simulate this case but it gives an idea of



(a) Xeon Pin 1



(b) Xeon Pin 3



(c) KNL Pin 1

Figure 8.7: NAS EP Class-C results.

how unequal PU speeds can be improved via weighted scheduling strategies.

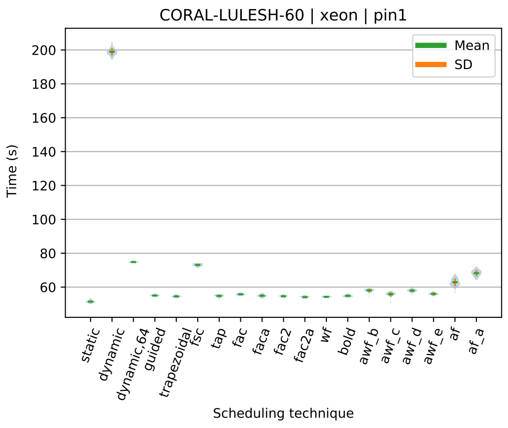
8.7 CORAL Benchmarks

The second set of tests stem from the CORAL and CORAL2 suites [49]. Two applications, Lulesh and Quicksilver, were chosen and, this time, a combination of MPI + OpenMP tests are done. Table 8.13 contains the selected applications and how they have been modified.

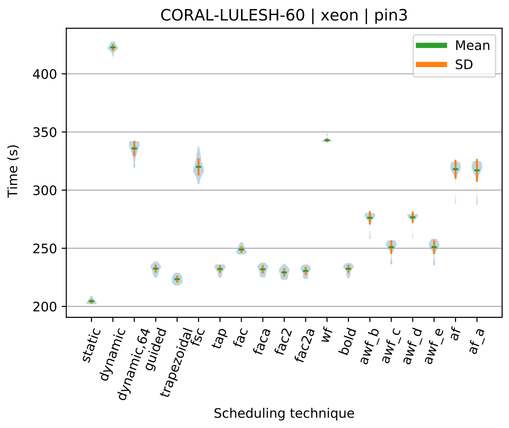
Table 8.13: CORAL Benchmarks details.

App	Size	Modified loop file/line	Description
Lulesh	60	lulesh.cc/810, lulesh.cc/1037, lulesh.cc/1538	Shock hydrodynamics for unstructured meshes. Fine-grained loop level threading.
Quicksilver	100000000 particles (OpenMP only), 10000000 particles (MPI + OpenMP)	mc_omp_parallel_for_schedule_static.hh/4	Monte Carlo transport benchmark with multi-group cross section lookups. Stresses memory latency, significant branching, and one large kernel that is 1000's of lines big.

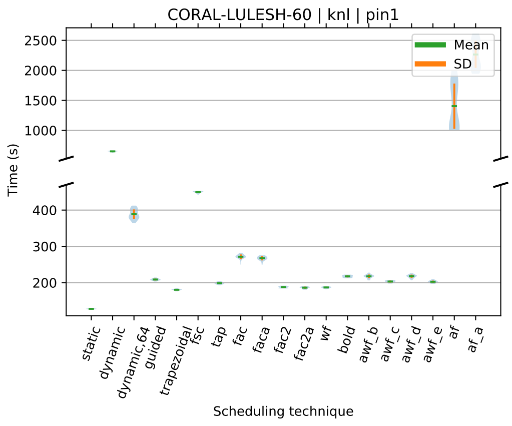
Static does a great job in Lulesh, performing the best on both platforms. Dynamic is about 4 times slower than static in Figure 8.8(a). When looking at Lulesh's profiling info in Table 8.9, the loop iterations definitely show execution time variance but the mean execution time is only 1 microsecond which could cause rather high overhead when scheduling individual and very small iterations, thus the bad performance with dynamic. But the other dynamic techniques, such as TAP, FAC, FAC2 or AWF are similarly fast as static which is a good mix of balance between load balance and scheduling overhead even when dealing with very short iterations. Quicksilver, on the other hand, does not really show a favorite scheduling technique, except for the non-hybrid version, see Figure 8.9(a), where dynamic is again the worst performer. One interesting thing here is again WF being the fastest with pin3 strategy that can be seen in Figure 8.9(d).



(a) Xeon Pin 1

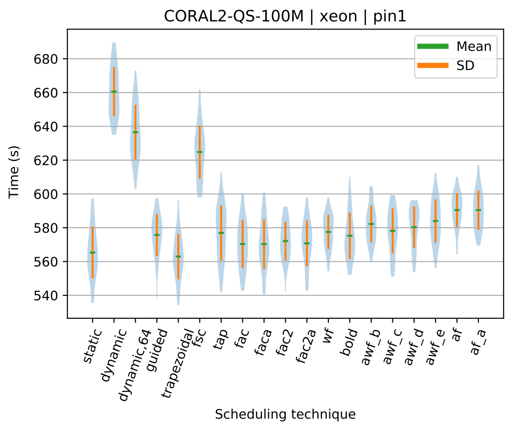


(b) Xeon Pin 3

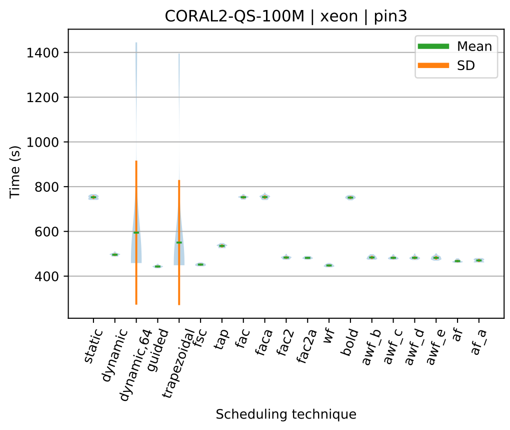


(c) KNL Pin 1

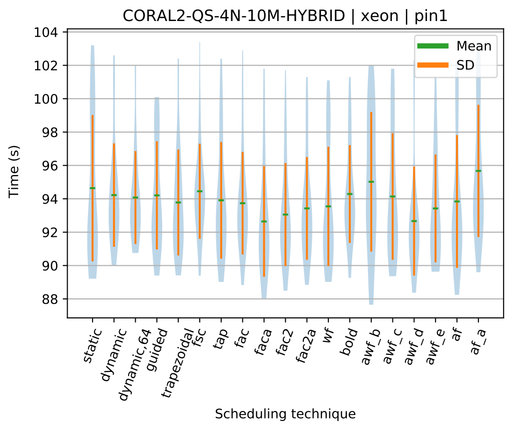
Figure 8.8: CORAL Lulesh results.



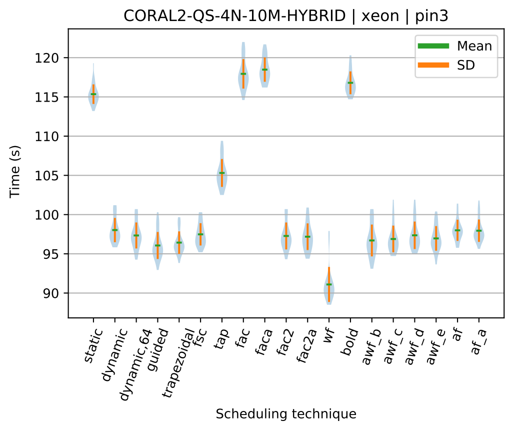
(a) Xeon Pin 1



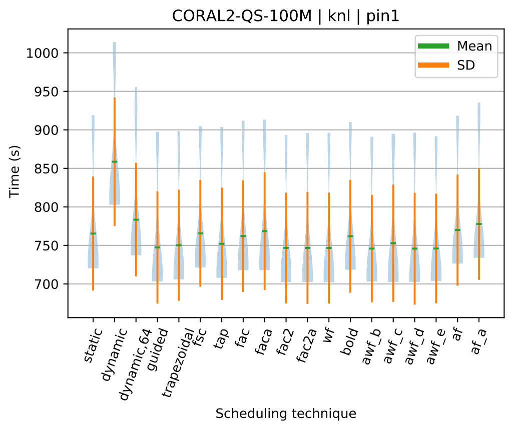
(b) Xeon Pin 3



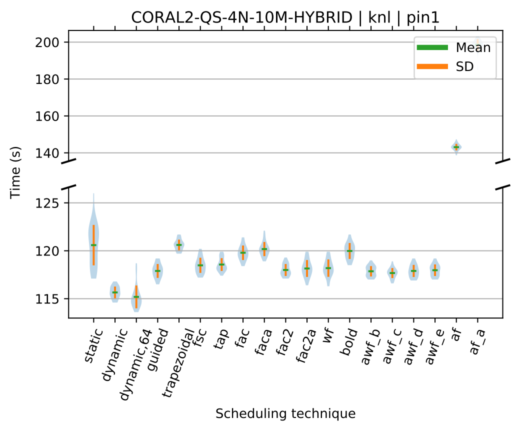
(c) Xeon Pin 1



(d) Xeon Pin 3



(e) KNL Pin 1



(f) KNL Pin 1

Figure 8.9: CORAL2 Quicksilver results. The hybrid version was tested on 4 nodes for both CPU types.

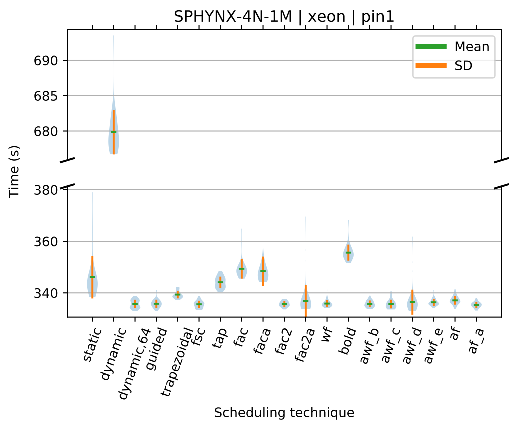
8.8 Sphynx and SPH-EXA

Sphynx [50] and SPH-EXA [51] are two applications which are developed and maintained at the University of Basel. The modifications and short descriptions can be seen in Table 8.15.

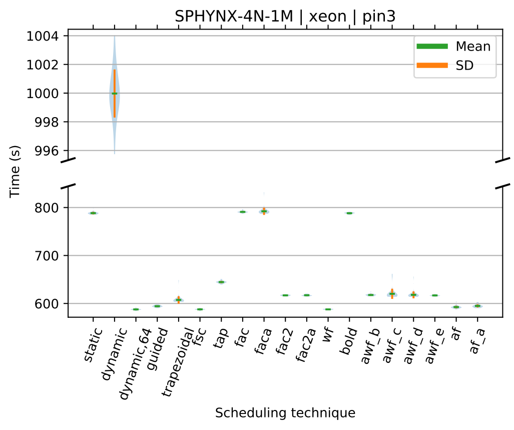
Table 8.15: SPH benchmarks details.

App	Size	Modified loop file/line	Description
Sphynx	1000000 particles	treewalkmod_grav_mefec.f90/104	An accurate density-based smoothed particle hydrodynamics (SPH) method for astrophysical applications.
SPH-EXA	-n 150 -s 5 -w -1	domain.hpp/40, MomentumEnergySqPatch.hpp/29	In this work an extensive study of three SPH implementations SPHYNX, ChaNGa, and XXX is performed, to gain insights and to expose any limitations and characteristics of the codes. These codes are the starting point of an interdisciplinary co-design project, SPH-EXA, for the development of an Exascale-ready SPH mini-app.

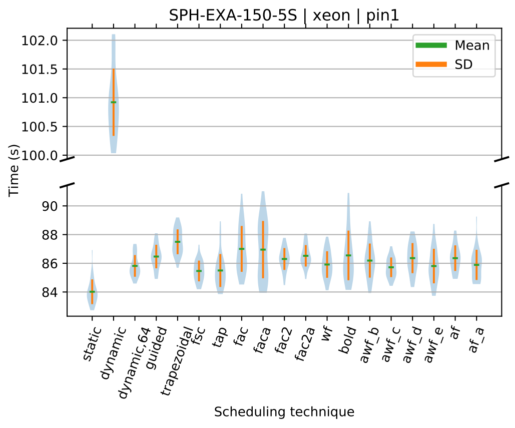
In both cases, Sphynx and SPH-EXA, the technique dynamic always is the worst with pin1 strategy. Especially in Sphynx on KNL, as depicted in Figure 8.10(e), it is very interesting to see that defining the chunk size of dynamic can improve the performance from, by far, the worst, to the best. This is once again a trial and error game to find the best fitting chunk size, as much as finding the best input values for strategies like FSC or BOLD. Other than that, all methods are similarly fast except for FAC being often slightly behind FAC2 and FAC2a which might be caused by the mutual exclusion overhead or not the best profiling information. Same accounts for BOLD that can suffer from bad profiling information.



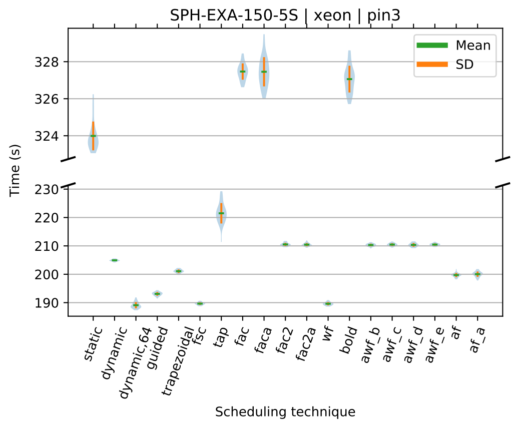
(a) Xeon Pin 1



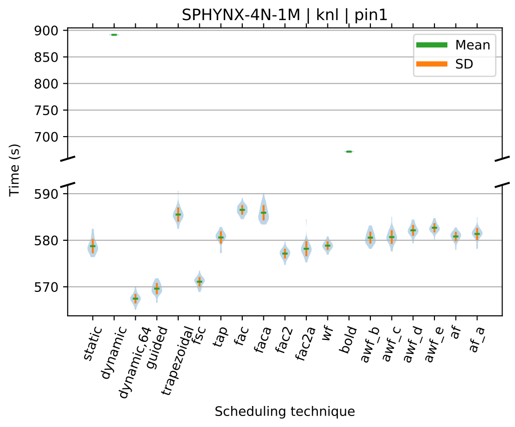
(b) Xeon Pin 3



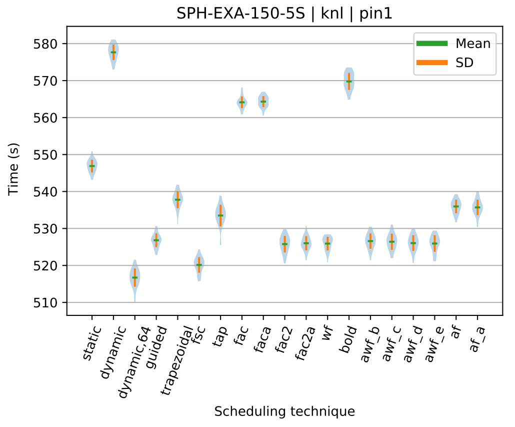
(c) Xeon Pin 1



(d) Xeon Pin 3



(e) KNL Pin 1



(f) KNL Pin 1

Figure 8.10: Sphynx and SPH-EXA results. Sphynx was tested in hybrid mode (MPI + OpenMP) on 4 nodes for both CPU types.

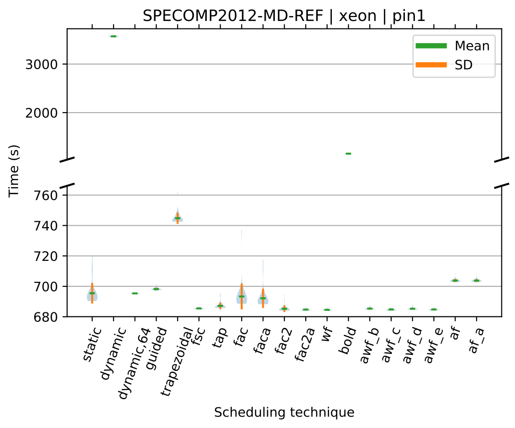
8.9 SPEC OMP 2012

SPEC OMP 2012 [12] is a very popular benchmark suite used by many companies such as Intel to benchmark their products. We have tested six applications from this suite with our DLS implementation. Table 8.17 lists all use applications and their modified loops.

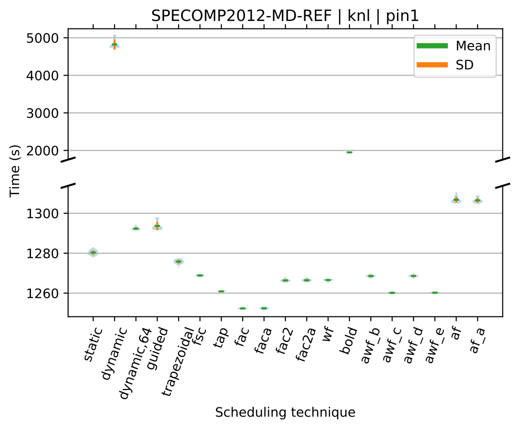
Table 8.17: SPEC OMP 2012 details.

App	Size	Modified loop file/line	Description
350md	ref	int_ion_mix_direct.f/84/41/132, int_ion_pure_direct.f/85/42/142, int_nn_direct.f/117/55/186	Physics: Molecular Dynamics
351bwaves	ref	block_solver.F/277, shell_lam.F/260, jacobian_lam.F/32	Physics: Computational Fluid Dynamics (CFD)
352nab	ref	eff.c/1992/2234/2948/2729/1732	Molecular Modeling
360ilbdc	ref	mod_relax.f90/52, ilbdc-kernel.f90/149/ 169/178, mod_benchgeo.f90/33	Lattic Boltzmann
362fma3d	ref	platq.f90/269	Mechanical Response Simulation
363swim	ref	swim.f/421/334/276	Weather Prediction

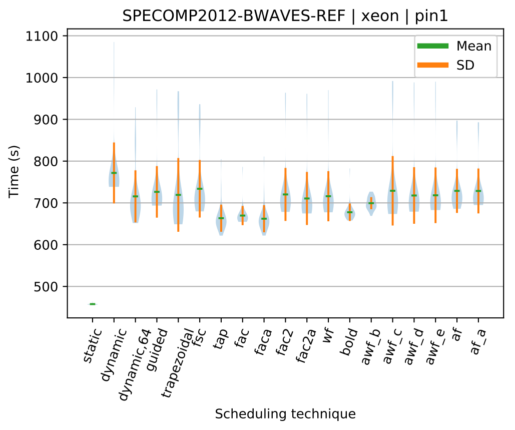
In application md, performed on KNL nodes, FAC and FACa are the fastest, even faster than their counterpart FAC2, that can be seen in Figure 8.11(b). Thinking of all the other results, this is a rather surprising outcome since FAC and FACa often lie slightly behind FAC2. One possible explanation could be the big number of 64 PUs a KNL processor comes with and FAC's batch size sharing nature among the threads which leads to less computation. When looking at the exact same application on Xeon in Figure 8.11(a), it is no longer the case that FAC is faster than FAC2. Xeon's less crowded 20 PUs and higher core processing speeds might not benefit that much from FAC's batch size sharing. Nevertheless, the problem with finding the best profiling information, which is required in FAC and FACa, could also be just luckily chosen. This issue of schedules requiring input values makes comparisons a lot harder. One of the highlights in SPEC can be found in nab in Figures 8.11(e) and 8.11(f) where static and dynamic are overwhelmingly outperformed by schedules like guided, FSC, FAC2, AWF variants and AF. Where static took almost 1000 seconds, FAC2 could finish in under 750 seconds. With KNL, the difference is even higher.
Another interesting result is depicted in 8.12(f), in which dynamic is faster than any other technique, which is rather a rare thing to observe. The same application on Xeon shows a completely different picture where static is by far the fastest technique. This example shows that not only the application itself but also the system can change the decision on which technique should be considered. Finally, in swim, see Figure 8.12(e), it is very well explainable that static is the fastest because when looking at this application's iteration times in Table 8.9, there is not much of variance compared to the mean execution time. In the case of KNL the difference is even higher, thus static being the leader.



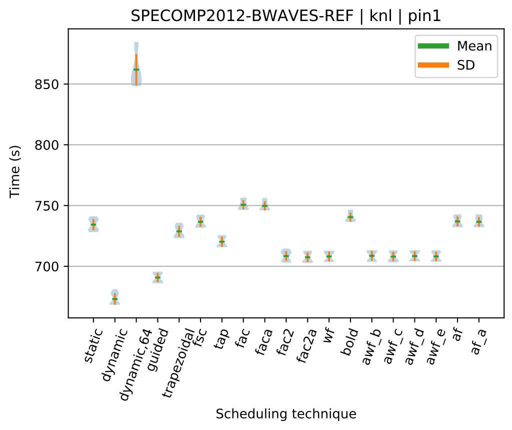
(a) Xeon Pin 1



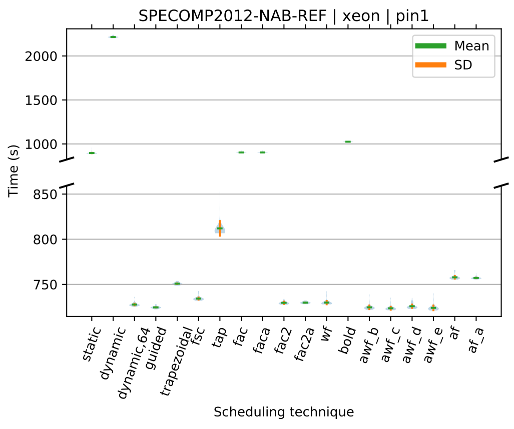
(b) KNL Pin 1



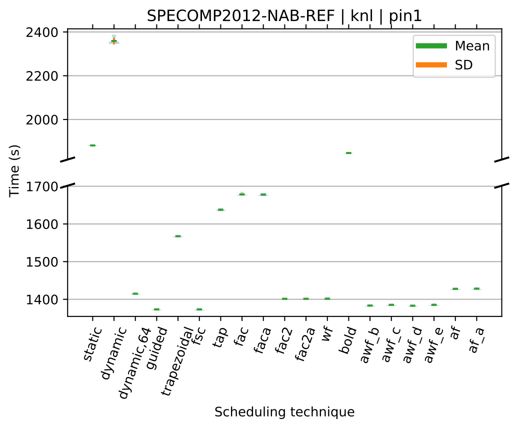
(c) Xeon Pin 1



(d) KNL Pin 1

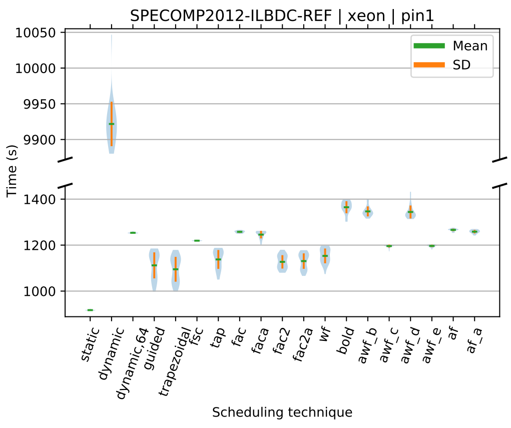


(e) Xeon Pin 1

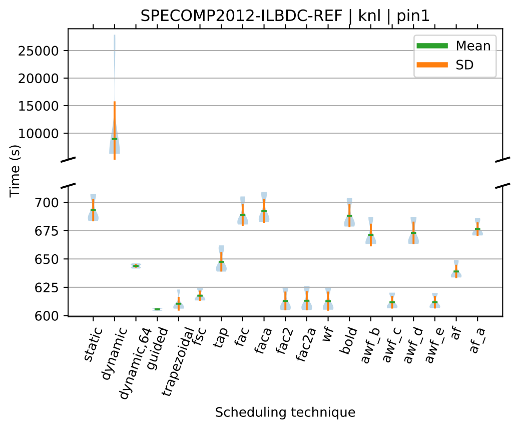


(f) KNL Pin 1

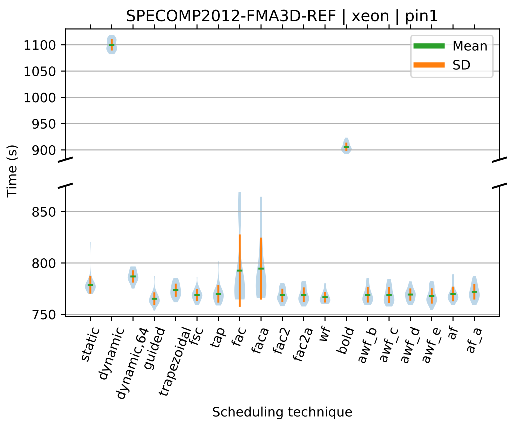
Figure 8.11: SPEC OMP 2012 350md, 351bwaves and 352nab results. These benchmarks were performed with pinning strategy 1 only.



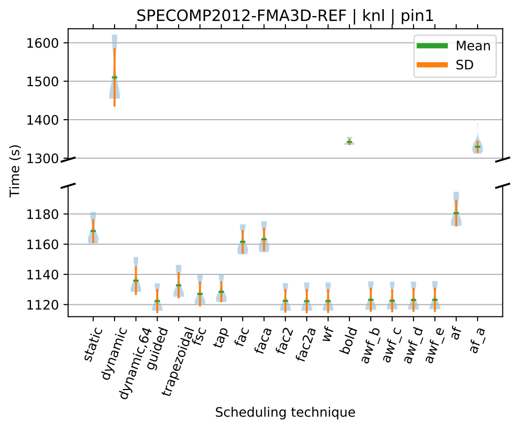
(a) Xeon Pin 1



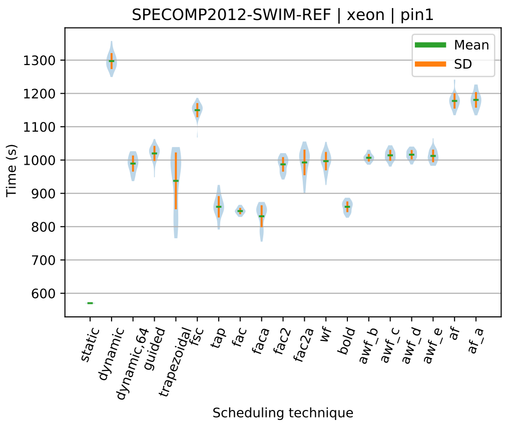
(b) KNL Pin 1



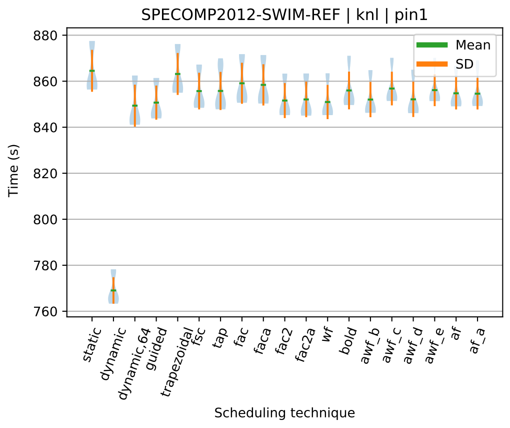
(c) Xeon Pin 1



(d) KNL Pin 1



(e) Xeon Pin 1



(f) KNL Pin 1

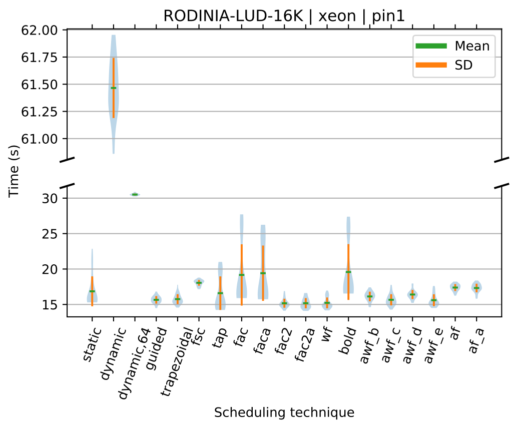
Figure 8.12: SPEC OMP 2012 360ilbdc, 362fma3d and 363swim results. These benchmarks were performed with pinning strategy 1 only.

8.10 Rodinia Benchmark Suite

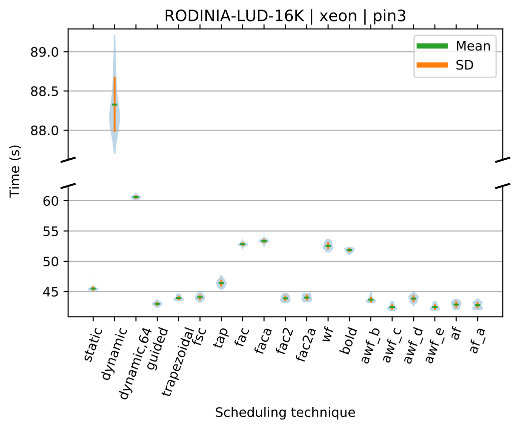
The applications lud and lavaMD are taken from the Rodinia benchmark suite 3.1 [9]. Table 8.19 shows the details and modified loops of the two chosen applications.

Table 8.19: Rodinia benchmark suite details.

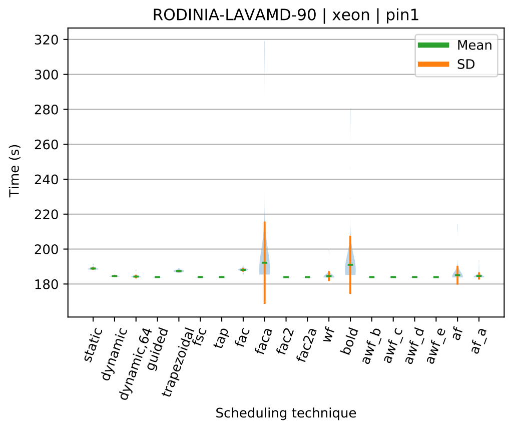
App	Size	Modified loop file/line	Description
lud	16000	lud_omp.c/123	Linear Algebra
lavaMD	90	kernel_cpu.c/112	Molecular Dynamics



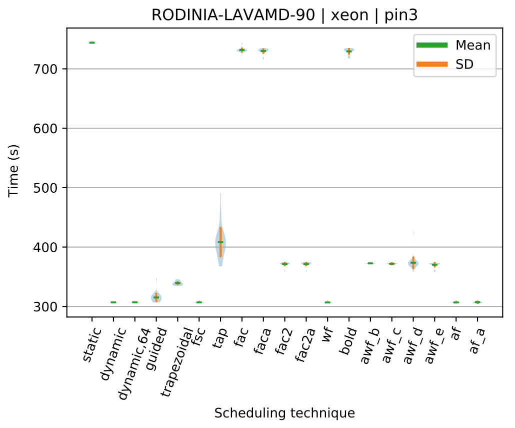
(a) Xeon Pin 1



(b) Xeon Pin 3



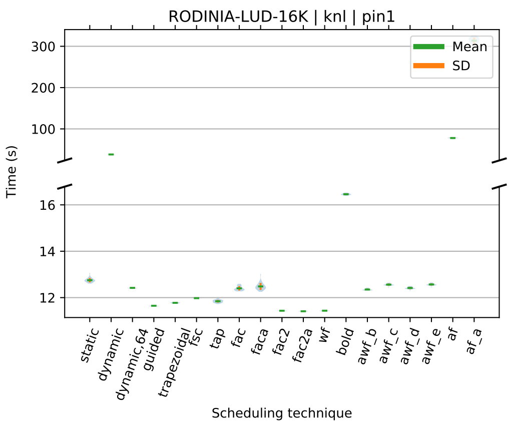
(c) Xeon Pin 1



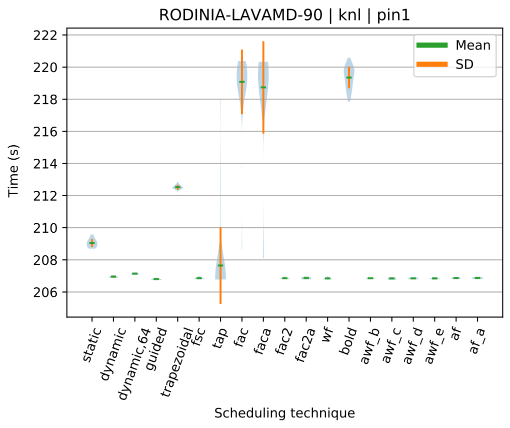
(d) Xeon Pin 3

Figure 8.13: Xeon results for Rodinia lud and lavaMD.

The newly implemented strategies perform all well in both Rodinia applications on Xeon. With lud on KNL, see Figure 8.14(a), AF marks an exception by being similarly slow as dynamic. Just like dynamic, AF also comes with a lot of overhead, especially when dealing with short but many iterations. Additionally, the results give an impressions that AF performs worse on the KNL platform than on Xeon.



(a) KNL Pin 1



(b) KNL Pin 1

Figure 8.14: KNL results for Rodinia lud and lavaMD.

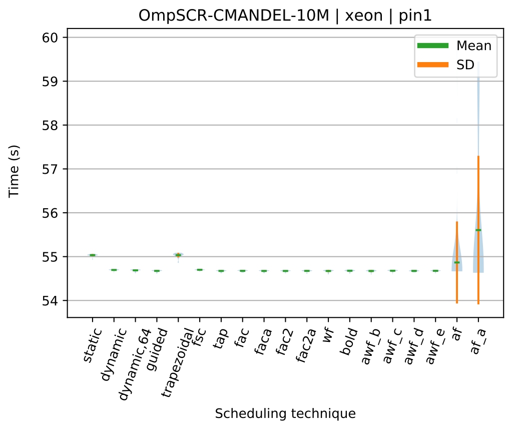
8.11 OmpSCR

From the suite OmpSCR [10] we have chosen cmandel and md for our experiments. Table 8.21 has more details about their modifications.

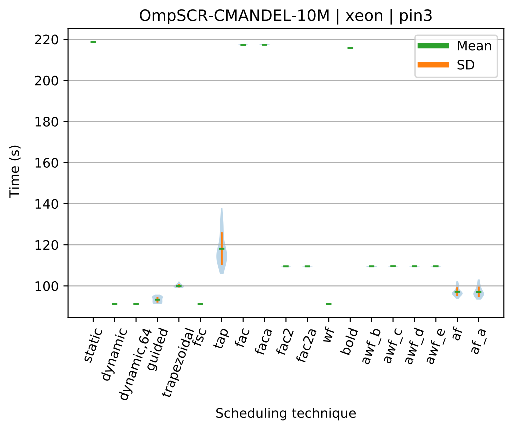
Table 8.21: OmpSCR benchmark suite details.

App	Size	Modified loop file/line	Description
cmandel	10000000 points	c_mandel.c/107	Mandelbrot
md	16384 particles, 1000 simulation steps	c_md.c/162	Molecular Dynamics

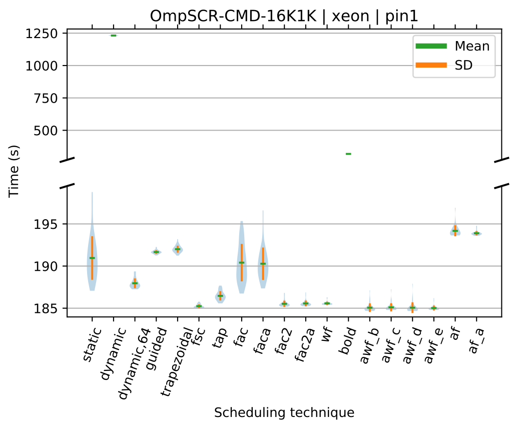
The newly implemented scheduling techniques FSC, TAP, FAC2 and AWF variants can shine in the application md on both CPU platforms as the Figures 8.15(c) and 8.15(f) show. On KNL, around 4% improvement to the fastest available scheduling technique, in this case guided, and 6% to static can be achieved by FSC and FAC2. The application cmandel, however, does not show any winner besides of AF having a very high variance. It is very interesting that from application to application, the results can vary so drastically and in some, all the techniques perform similarly.



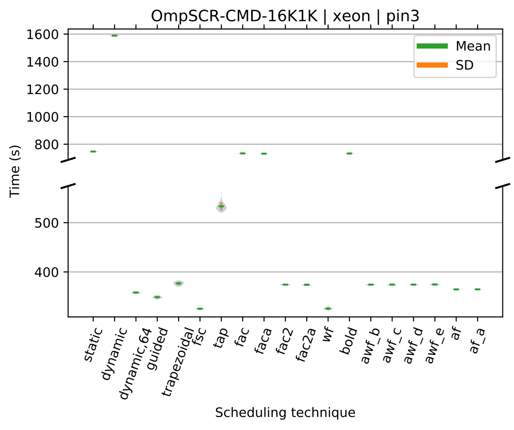
(a) Xeon Pin 1



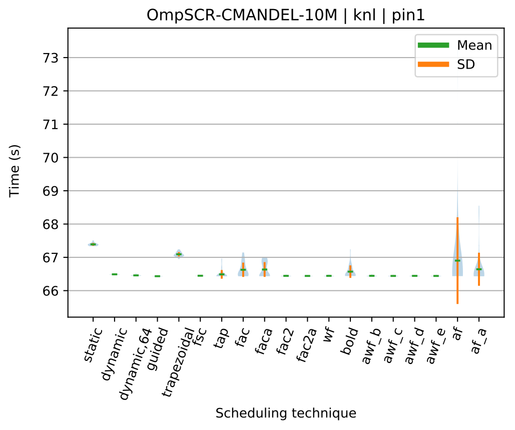
(b) Xeon Pin 3



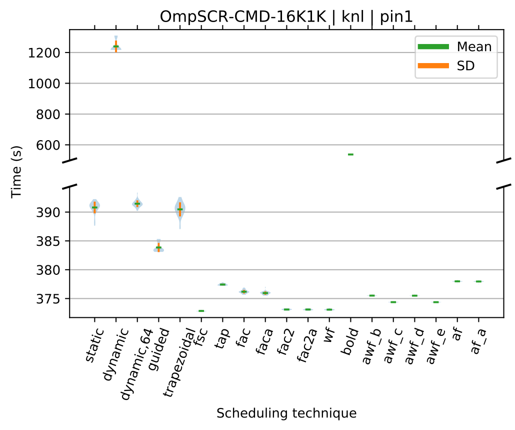
(c) Xeon Pin 1



(d) Xeon Pin 3



(e) KNL Pin 1



(f) KNL Pin 1

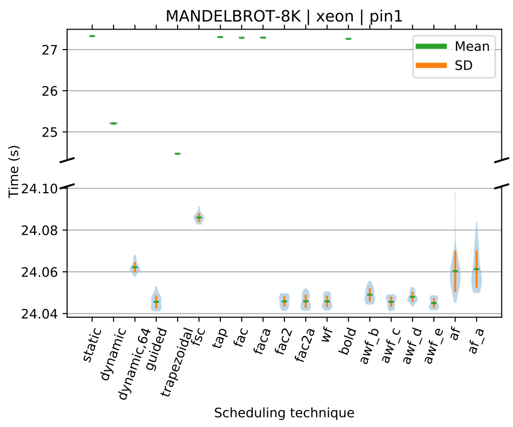
Figure 8.15: OmpSCR cmandel and md results.

8.12 Mandelbrot and Adjoint Convolution

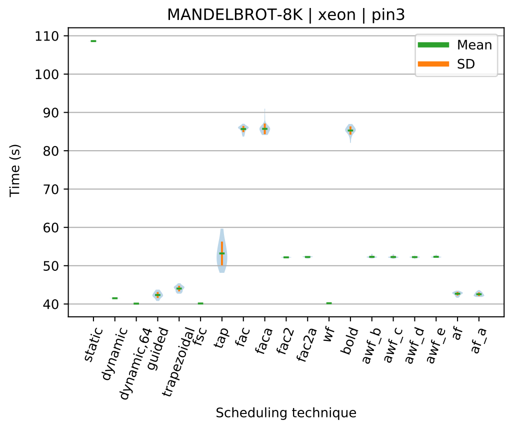
The last two applications stem from a freely available source and are called MANDELBROT [52] and AC [53]. Table 8.23 has more details about the two applications.

Table 8.23: MANDELBROT and AC details.

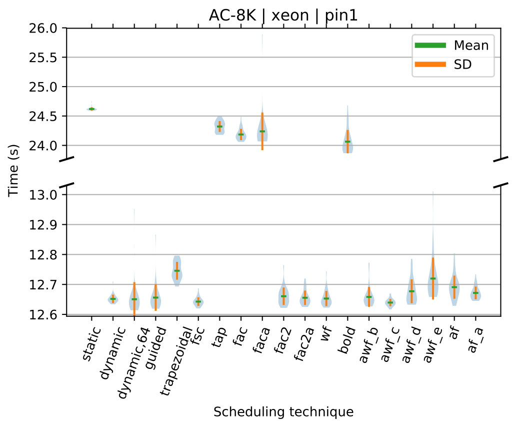
App	Size	Modified loop file/-line	Description
MANDELBROT	-x_pix 8000 -y_pix 8000	mb_1D_collapsed.c/ 136	Mandelbrot
AC	matrix size = 1000	ac.c/49	Adjoint Convolution



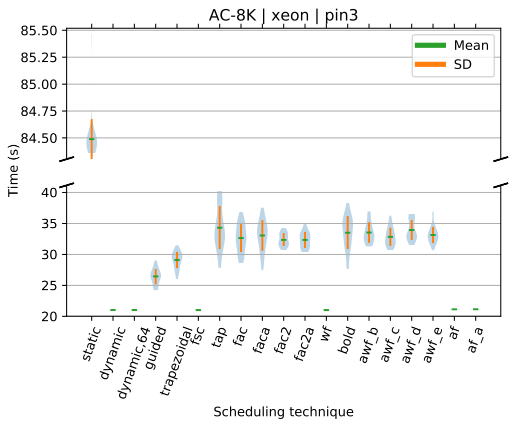
(a) Xeon Pin 1



(b) Xeon Pin 3



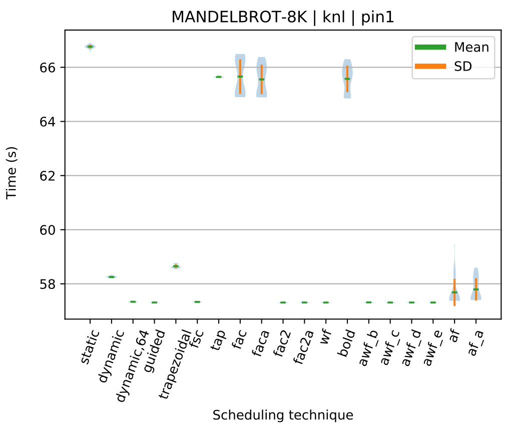
(c) Xeon Pin 1



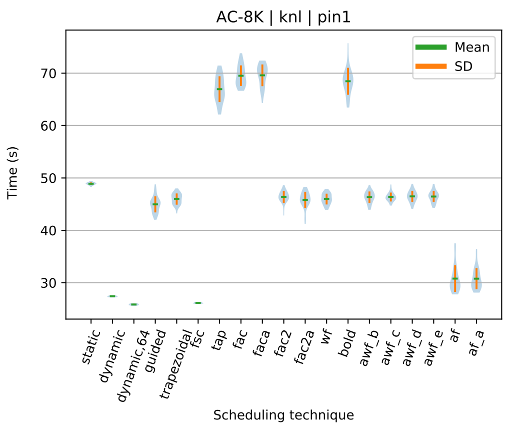
(d) Xeon Pin 3

Figure 8.16: Xeon results for MANDELBROT and AC.

The first thing to say about MANDELBROT and AC is that static is always a bad choice in every case. These two applications really show that DLS techniques can't be avoided if performance demands are critical. In every pin1 case, the techniques FAC2 and AWF



(a) KNL Pin 1



(b) KNL Pin 1

Figure 8.17: KNL results for MANDELBROT and AC.

variants belong to the best performers. The same is true for guided. With pin3 strategy, the technique WF is again faster than its non-weighted version FAC2.

8.13 Random Sleep

For experiment reasons, a very small and synthetic application was written in this thesis (see source in Appendix B) to give dynamic a better chance, showing its strength. This application consists of a single parallel loop that contains 10000 iterations and is repeated 10 times. The loop simply lets a thread wait for a uniformly distributed random time variable between 1 to 6000 microseconds for the first 10% of iterations. The remaining 90% of iterations let the thread wait for 1 to 6 microseconds, thus, having a much higher variance in the beginning of the loop. It is very interesting to see that, besides dynamic and AF, even FSC can achieve a very good performance with the right input values. Guided, trapezoidal and factoring techniques perform still twice as fast as static.

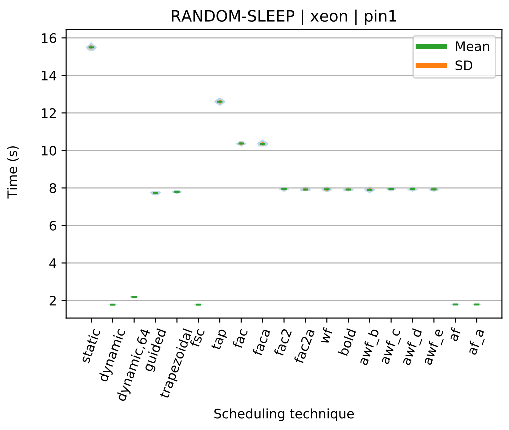


Figure 8.18: Xeon results for Random Sleep with pin1 strategy.

9 Conclusion and Future Work

We have implemented 11 new DLS techniques into libomp and tested them with 24 different benchmark applications. We have shown that not one specific scheduling technique fits for all cases. Depending on the chosen application and its loop characteristics, either static methods or certain dynamic ones achieve the best performance. The available OpenMP scheduling techniques, static, dynamic and guided do not reach the best performance in every application and system. New systems with many, more complex and heterogeneous processing units, could benefit from adaptive or weighted strategies. This thesis gives an example with its implementation and wants to motivate future OpenMP versions to allow and include new scheduling techniques.

The results have shown that every strategy has its strengths and weaknesses. In the case of dynamic (or SS), it is almost never a good choice since it produces too much overhead. It was one of the worst performers when looking at this thesis' results. However, in irregular applications with long iteration execution times, such as SPEC OMP 2012's swim application, and especially when ran on KNL with 64 PUs, dynamic could outperform every other scheduling strategy. Irregular loop iteration times do not mean that dynamic is the best choice since it also depends on the system, number of iterations, their mean execution times and data locality demands. Very small iterations, but large in their amount, can produce extreme overhead with dynamic as seen with Lulesh. Additionally, since threads pick single iterations randomly, the effect of data locality is lost. By specifying the chunk size to 64 or another desired size, you can reduce dynamic's overhead and improve data locality within a chunk.

When looking at the factoring methods, almost in all cases, FAC2 performed better than FAC. This can be justified by the fact that FAC uses mutual exclusion in its scheduling algorithm and it relies on *good* profiling info where FAC2 uses a less complex algorithm with faster atomic function calls instead of mutual exclusion and there is no need for profiling information. In general, FAC2 produced very good results across all applications and platforms. One could say, if you don't know what to choose, take FAC2. The adaptive weighted factoring techniques have shown similar speeds as FAC2.

Two different pinning strategies were presented in this thesis, to test the weighted and adaptive DLS techniques and how they interact with overloaded PUs. The results have

shown that WF is almost always faster than its identical counterpart FAC2a but without the weights. This shows that the weights can help to improve load balance when the system has certain unequal PU speeds or other constant systemic load imbalance. AF could also lead to better performance with overloaded PUs in pin3 strategy. With heterogeneous PUs it could show even more of its adaptive strength. We could not measure a benefit of AWF with pin3 strategy compared to FAC2 but if different PU speeds were available, this could have given another picture.
Strategies like FSC, TAP, FAC and BOLD require profiling information which is a critical part to make them work as intended. The results show that BOLD is often a bad performer because of its bad input data. At the same time, FSC could outperform every technique, even static, when using good input data. The process of finding them, however, is extremely difficult and time consuming since the application must be profiled prior to runtime.

For the future, it would be interesting to see if scheduling techniques could be implemented by the user itself and used by the compiler. There is ongoing work in this area, also called *User Defined Scheduling* or UDS. By allowing the user providing these techniques, one could take this thesis' implementation and use it without the need of a compiler or runtime that must implement it. Talking about compilers, one possible work could be to implement all the DLS methods, provided by this thesis, into the compiler itself so that the technique can be chosen as static or guided. Other work could be to make this implementation production ready and push back into the official libomp repository to make it available for everyone. For this, however, a few changes might be needed since this thesis did use a few components, such as std::vector or std::mutex, from the C++ standard library. By resolving these dependencies and using optimized functions provided by libomp itself, the compatibility would be maintained. A very interesting topic would be to test this implementation on heterogeneous systems with truly different processing unit speeds, not just an unbalanced pinning strategy, and see what the weighted and adaptive techniques perform. The technique fractiling was not implemented in this thesis due the expected high overhead in its work-stealing (or borrowing) feature. Nevertheless, it would be interesting to see if fractiling can improve performance with its data locality usage on shared memory systems. Finally, to tackle an issue with multiple and different loops inside an application and the techniques that require profiling information, it would be interesting to find a way of giving multiple input values, one for each loop, that then can be used by the runtime for the particular loops. The libomp version in this thesis does only allow profiling information for one single loop. Strategies like FSC, FAC, TAP and BOLD could benefit from multiple input values.

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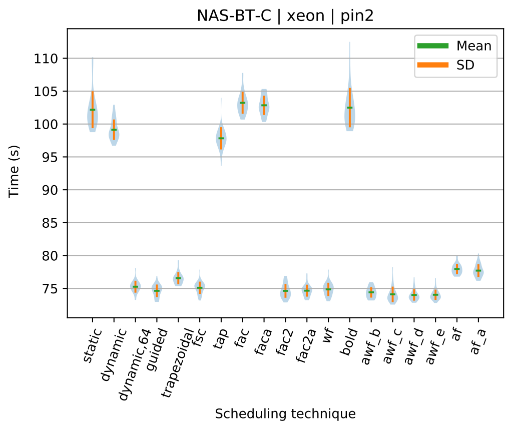
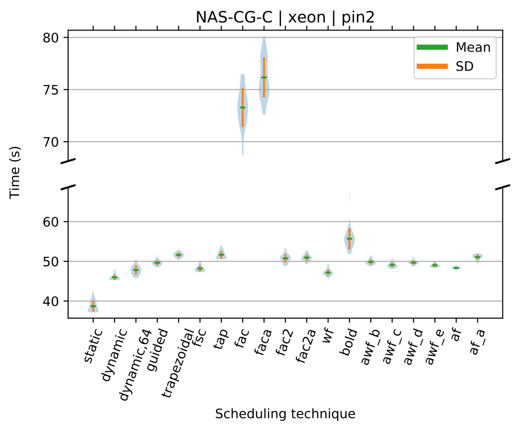
A
Pin2 Results

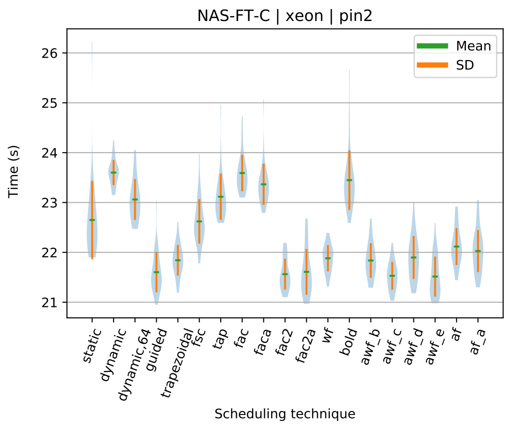
Here are the results of pin2 strategy. This thesis does not comment on these because of pin2's non-fixed thread-to-core binding. For completeness reasons, it is included here.



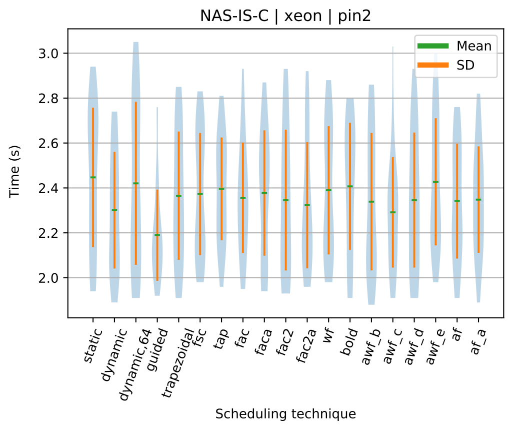
(a) Xeon Pin 2



(b) Xeon Pin 2

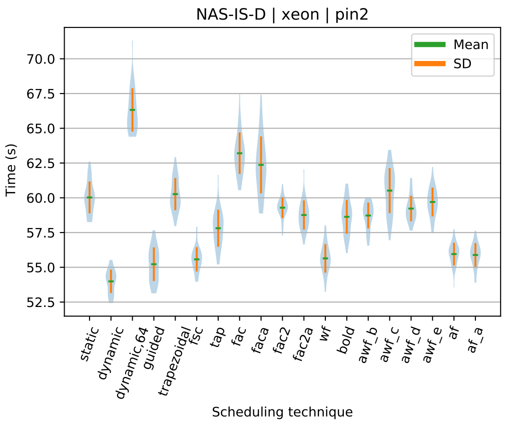


(c) Xeon Pin 2

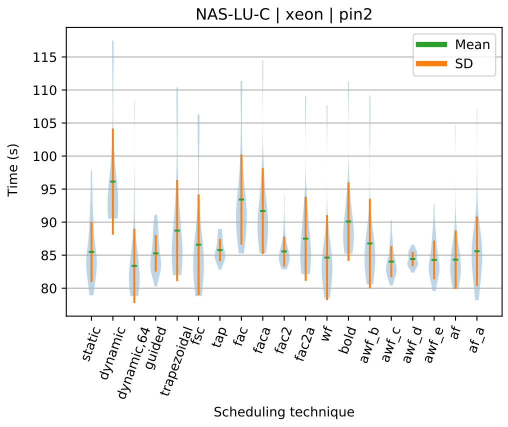


(d) Xeon Pin 2

Figure A.1: NAS BT, CG, FT and IS-C results with pin2 strategy.



(a) Xeon Pin 2



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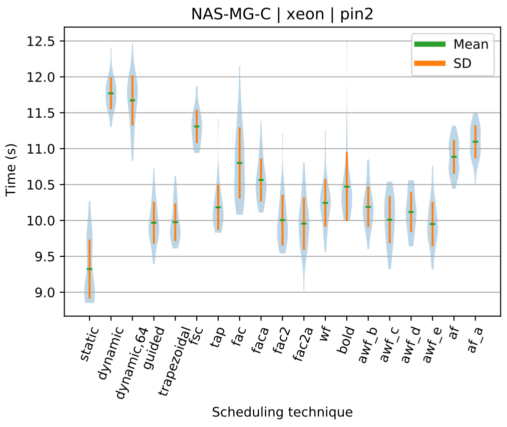
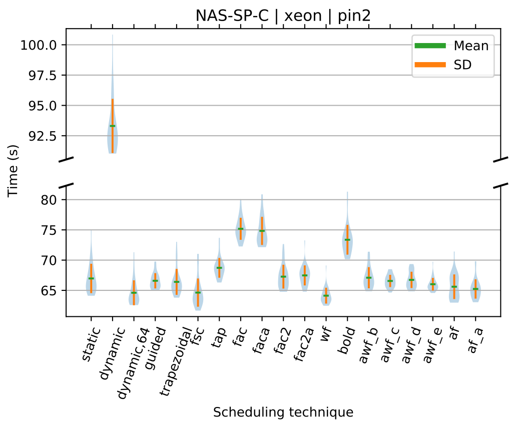
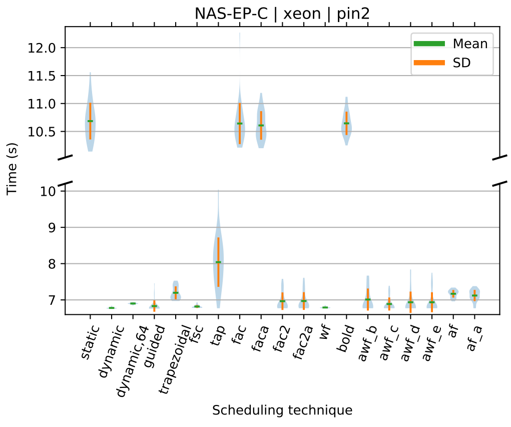


(c) Xeon Pin 2

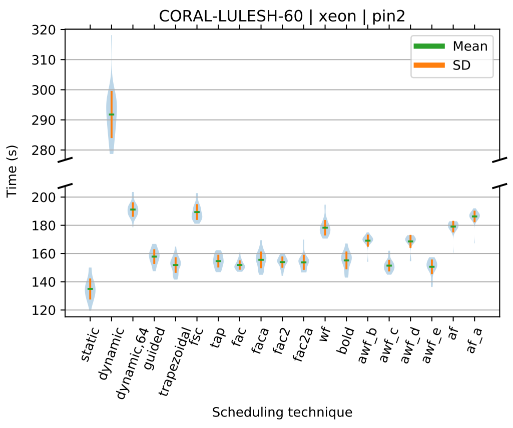


(d) Xeon Pin 2

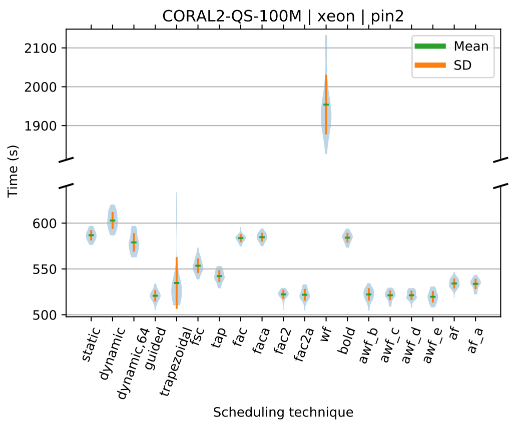


(e) Xeon Pin 2

Figure A.2: NAS IS-D, LU, MG, SP and EP results with pin2 strategy.



(a) Xeon Pin 2



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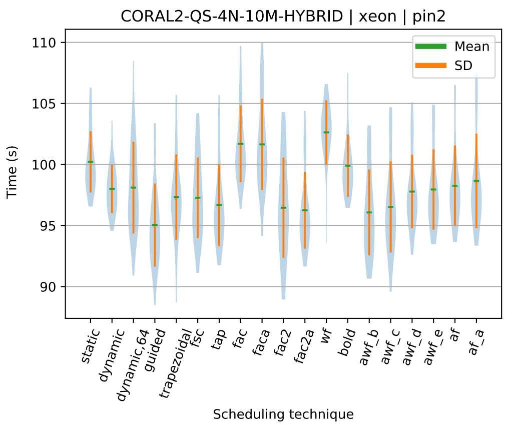
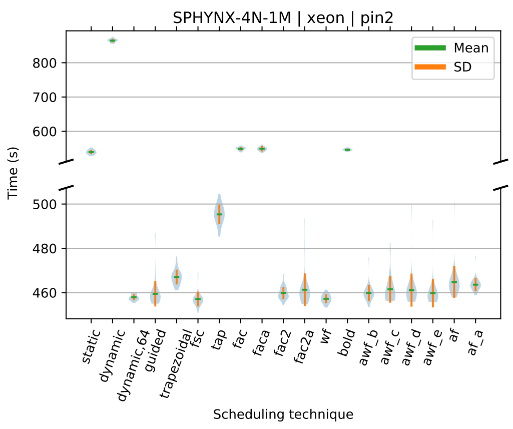
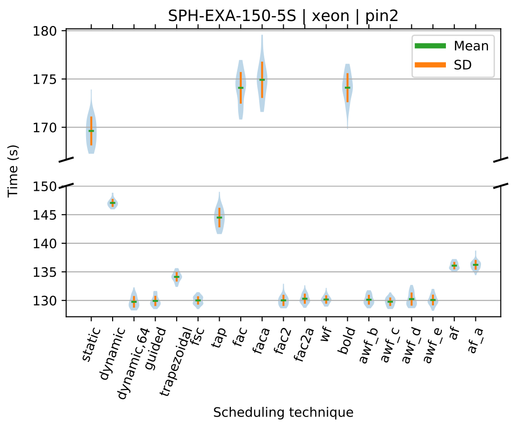


(c) Xeon Pin 2

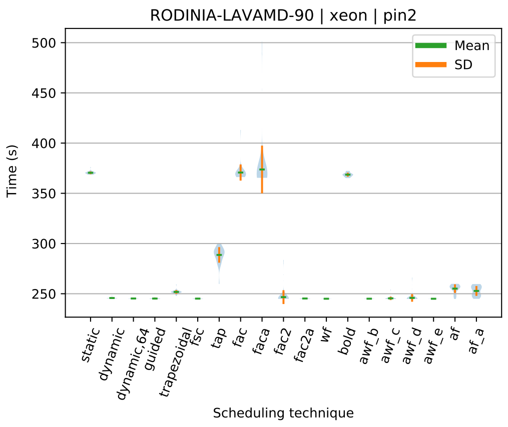


(d) Xeon Pin 2

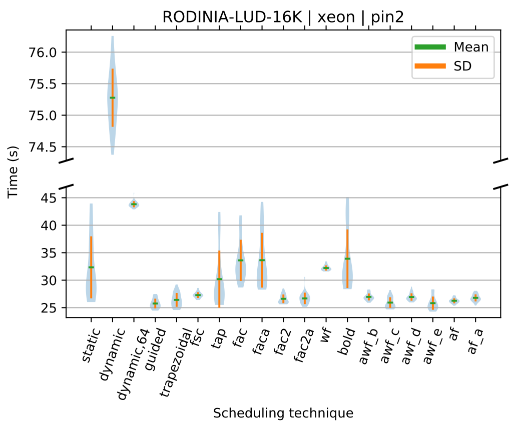


(e) Xeon Pin 2

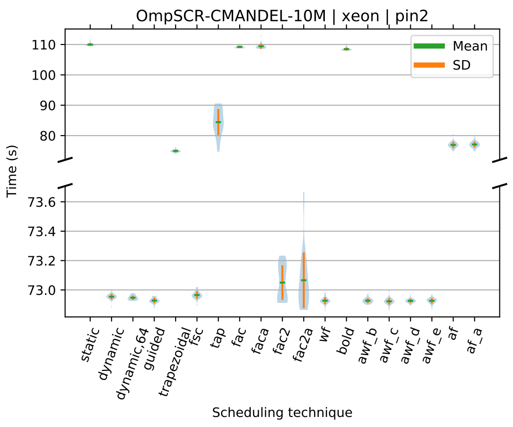
Figure A.3: CORAL, Sphynx and SPH-EXA pin2 results.



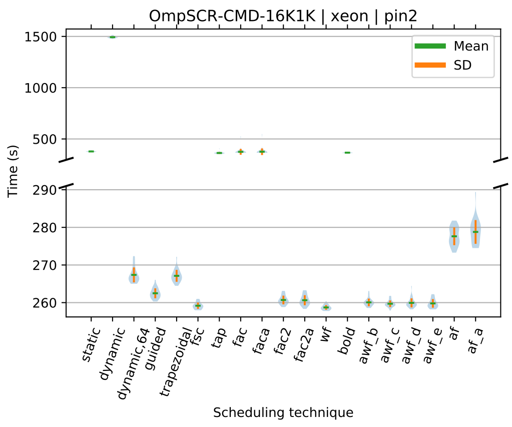
(a) Xeon Pin 2



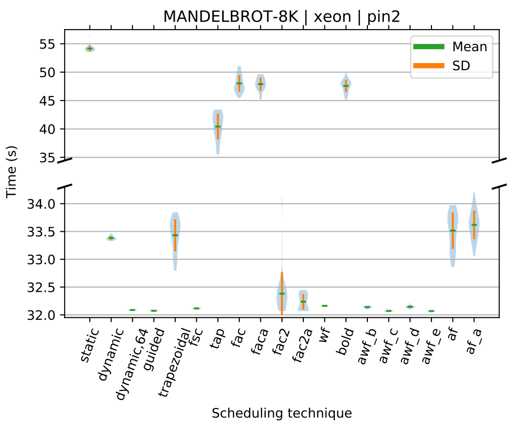
(b) Xeon Pin 2



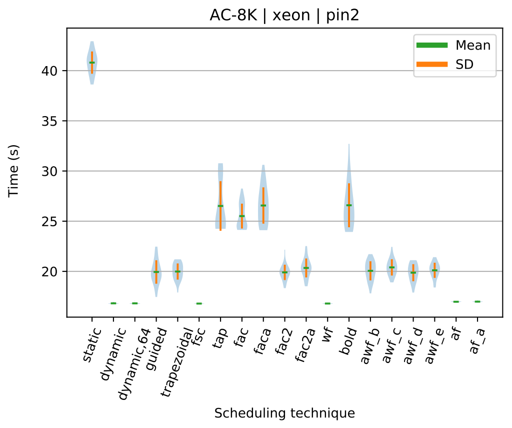
(c) Xeon Pin 2



(d) Xeon Pin 2



(e) Xeon Pin 2



(f) Xeon Pin 2

Figure A.4: Results for Rodinia, OmpSCR, MANDELBROT and AC with pin2 strategy.

B
Random Sleep

```
#include <thread>
#include <random>
#include <chrono>
#include <iostream>
#include <omp.h>

int main()
{
   const long size = 10000;
   const int reps = 10;
   double start, end, time;

   std::mt19937_64 eng{std::random_device{}()};
   std::uniform_int_distribution<> dist1{1, 6000};
   std::uniform_int_distribution<> dist2{1, 6};

   start = omp_get_wtime();
#pragma omp parallel shared(eng, dist1, dist2)
   {
      for (int i = 0; i < reps; i++)
      {
#pragma omp for schedule(runtime)
         for (long n = 0; n < size; ++n) {
            if (n < size * 0.1)
               std::this_thread::sleep_for(std::chrono::
                  ↪ microseconds{dist1(eng)});
            else
               std::this_thread::sleep_for(std::chrono::
                  ↪ microseconds{dist2(eng)});
         }
```

```
        }
    }
    end = omp_get_wtime();
    time = end - start;
    std::cout << "Time:␣" << time << "␣seconds.\n";
}
```

Declaration on Scientific Integrity
Erklärung zur wissenschaftlichen Redlichkeit

includes Declaration on Plagiarism and Fraud
beinhaltet Erklärung zu Plagiat und Betrug

Author — Autor
Akan Yilmaz

Matriculation number — Matrikelnummer
10-927-473

Title of work — Titel der Arbeit
Implementation of Scheduling Algorithms in an OpenMP Runtime Library

Type of work — Typ der Arbeit
Master Thesis

Declaration — Erklärung
I hereby declare that this submission is my own work and that I have fully acknowledged the assistance received in completing this work and that it contains no material that has not been formally acknowledged. I have mentioned all source materials used and have cited these in accordance with recognised scientific rules.

Hiermit erkläre ich, dass mir bei der Abfassung dieser Arbeit nur die darin angegebene Hilfe zuteil wurde und dass ich sie nur mit den in der Arbeit angegebenen Hilfsmitteln verfasst habe. Ich habe sämtliche verwendeten Quellen erwähnt und gemäss anerkannten wissenschaftlichen Regeln zitiert.

Basel, 30.06.2019

Signature — Unterschrift