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Auto-tuned OpenCL kernel co-execution in OmpSs for heterogeneous systems

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ABSTRACT

The emergence of heterogeneous systems has been very notable recently. The nodes of the most powerful computers integrate several compute accelerators, like GPUs. Profiting from such node configurations is not a trivial endeavour. OmpSs is a framework for task based parallel applications, that allows the execution of OpenCl kernels on different compute devices. However, it does not support the co-execution of a single kernel on several devices. This paper presents an extension of OmpSs that rises to this challenge, and presents Auto-Tune, a load balancing algorithm that automatically adjusts its internal parameters to suit the hardware capabilities and application behavior. The extension allows programmers to take full advantage of the computing devices with negligible impact on the code. It takes care of two main issues. First, the automatic distribution of datasets and the management of device memory address spaces. Second, the implementation of a set of load balancing algorithms to adapt to the particularities of applications and systems. Experimental results reveal that the co-execution of single kernels on all the devices in the node is beneficial in terms of performance and energy consumption, and that Auto-Tune gives the best overall results.

1. Introduction

The undeniable success of computing accelerators in the supercomputing scene nowadays, is not only due to their high performance, but also due to their outstanding energy efficiency. Interestingly, this success comes in spite of the fact that efficiently programming machines with these devices is far from trivial. Not long ago, the most powerful machines would have a set of identical processors. To further increase the computing power, now they are sure to integrate some sort of accelerator device, like GPGPUs or Intel Xeon Phi. In fact, architects are integrating several such devices in the nodes of recent HPC systems. The trend nowadays is towards highly heterogeneous systems, with computing devices of very different capabilities. The challenge for the programmers is to take full advantage of this vast computing power.

But it seems that the rapid development of heterogeneous systems has caught the programming language stakeholders unaware. As a result, there is a lack of a convenient language, or framework, to fully exploit modern multi-GPU heterogeneous systems, leaving the programmer to face these complex systems alone.

It is true that several frameworks exist, like CUDA [24] and OpenCL [34], that can be used to program GPUs. However, they all regard heterogeneous systems as a collection of independent devices, and not as a whole. These enable programmers to access the computing power of the devices, but do not help them to squeeze all the performance out of the heterogeneous system, as each device must be handled independently. Guided by the host-device model introduced by these frameworks, programmers usually offload tasks, or kernels, to accelerator devices one at a time. Meaning that during the completion of a task the rest of the machine is left idle. Hence, the excellent performance of these machines is tarnished by an energy efficiency lower than could be expected. With several devices in one system, using only one at a time is a considerable waste. Some programmers have seen this flaw, and have tried to divide the computing tasks among all the devices of the system [4,14,27]. But it is an expensive path in terms of coding effort, portability and scalability.

This paper proposes the development of a means to assist the programmer with this task. Even leaving code length and complexity considerations aside, load balancing data-parallel applications on heterogeneous systems is a complex and multifaceted problem. It requires deciding what portions of the data-set of a given kernel

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are offloaded to the different devices, so that they all complete it at the same time [3,12,39].

To achieve this, it is necessary to consider the behavior of the kernels themselves. When the data-set of a kernel is divided in equally sized portions, or packages, it can be expected that each one will require the same execution time. This happens in well behaved, *regular* kernels but it is not always the case. The execution time of the packages of some kernels may have a wide variation, or even be unpredictable. These are considered *irregular* kernels. If how to balance a regular kernel can be decided prior to the execution, achieving near optimal performance, the same cannot be said about irregular ones. Their unpredictable nature forces the use of a dynamic approach that marshals the different computing devices at execution time. This however, increases the number of synchronization points between devices, which will have some overhead, reducing the performance and efficiency of the system. In conclusion, the diverse nature of kernels prevents the success of a single data-division strategy in maximizing the performance and efficiency of a heterogeneous system.

Aside from kernel behavior, the other key factor for load distribution is the configuration of the heterogeneous system. For the load to be well balanced, each device must get the right amount of work, adapted to the capabilities of the device itself. Therefore, a work distribution that has been hand-tuned for a given system is likely to underperform on a different one.

The OmpSs programming model is an ideal starting point in the path to hassle-free kernel co-execution. It provides support for task parallelism due to its benefits in terms of performance, cross-platform flexibility and reduction of data motion [8]. The programmer divides the code in interrelating tasks and OmpSs essentially orchestrates their parallel execution maintaining their control and data dependences. To that end, OmpSs uses the information supplied by the programmer, via code annotations with pragmas, to determine at run-time which parts of the code can be run in parallel. It enhances OpenMP with support for irregular and asynchronous parallelism, as well as support for heterogeneous architectures. OmpSs is able to run applications on symmetric multiprocessor (SMP) systems with GPUs, through OpenCL and CUDA APIs [31].

However, OmpSs can only assign kernels to single devices, therefore not supporting co-execution of kernels. An experienced programmer could decompose the kernel in smaller tasks so that OmpSs could send them to the devices. But there would be no guarantee that the resources would be efficiently used or the load properly balanced. The programmer would also be left alone in terms of dividing the input data and combining partial results. This would lead to longer code, which would be harder to maintain.

As a solution to the above problems this article presents an OmpSs extension which enables the efficient co-execution of massively data-parallel OpenCL kernels in heterogeneous systems. This has the advantage of providing a natural way to program using all the available resources that was not previously available in OmpSs. Manually achieving an equivalent functionality would require re-thinking the applications themselves to account for the heterogeneous devices, creating different tasks with adequate granularities and even implementations. Moreover, these extra manual work would need to be repeated if the system configuration changed. By automatically using all the available resources, regardless of their number and characteristics, the proposed extension presents an easy way to perform kernel co-execution and extracting the maximum performance of these systems. It takes care of load balancing, input data partitioning and output data composition.

The experimental results presented here show that, for all the used benchmarks, being able to co-execute kernels on multiple devices has a positive impact on performance. In fact, the results indicate that it is possible to reach an efficiency of the heterogeneous system over 0.85. Furthermore, the results also show that, although the systems exhibit higher power demand, the shorter execution time grants a notable reduction in the energy consumption. Indeed, the average energy efficiency improvement observed is 53%.

The main contributions of this article are the following:

- The OmpSs programming model is extended with a new scheduler, that allows a single OpenCL kernel instance to be co-executed by all the devices of a heterogeneous system.
- The scheduler implements two classic load balancing algorithms, Static and Dynamic, for regular and irregular applications.
- Aiming to give the best performance on both kinds of applications, two new algorithms are presented, HGuided and AutoTune, which is a parameterless version of the former.
- An exhaustive experimental study is presented, that corroborates that using the whole system is beneficial in terms of energy consumption as well as performance.

The remainder of this paper is organized as follows. Section 2 presents background concepts key to the understanding of the paper. Next, Section 3 describes the details of the load balancing algorithms. It is followed by Section 4, that covers the implementation of the OmpSs extension. Section 5 presents the experimental methodology and discusses its results. Finally, Section 7 offers some conclusions and future work.

2. Background

This section explains the main concepts of the OmpSs programming model that will be used throughout the remainder of the article.

OmpSs is a programming model based on OpenMP and StarSs, which has been extended in order to allow the inclusion of CUDA and OpenCL kernels in Fortran and C/C++ applications, as a simple solution to execute on heterogeneous systems [8,31]. It supports the creation of data-flow driven parallel programs that, through the asynchronous parallel execution of tasks, can take advantage of the computing resources of a heterogeneous machine. The programmer declares the tasks through compiler directives (pragma) in the source code of the application. These are used at runtime to determine when the tasks may be executed in parallel.

OmpSs is built on top of two tools:

- *Mercurium* is a source-to-source compiler that processes the high-level directives, and transforms the input code into a parallel application [21]. In this manner, the programmer is spared of low level details like the thread creation, synchronization and communication, as well as the offloading of kernels in a heterogeneous system.
- *Nanos++* is a run-time library that provides the necessary services for the execution of the parallel program [22]. Among others, these include task creation and synchronization, but also data marshaling and device management.

In the pragma annotations, the programmer specifies the data dependences between the tasks. Then, when the execution of the parallel program commences, a thread pool is created. Of these, only the master thread is active, and uses the services of the run-time library to generate tasks, identified by work descriptors, and adding them to a dependence graph. The master thread then schedules the execution of the tasks to the threads in the pool as soon as their input dependences are satisfied.

In terms of heterogeneous systems, OmpSs provides a *target* directive that indicates a set of devices in which a given task can run. In addition to a task, the target directive can be applied to a function definition. OmpSs also offers the *ndrange* clause that,

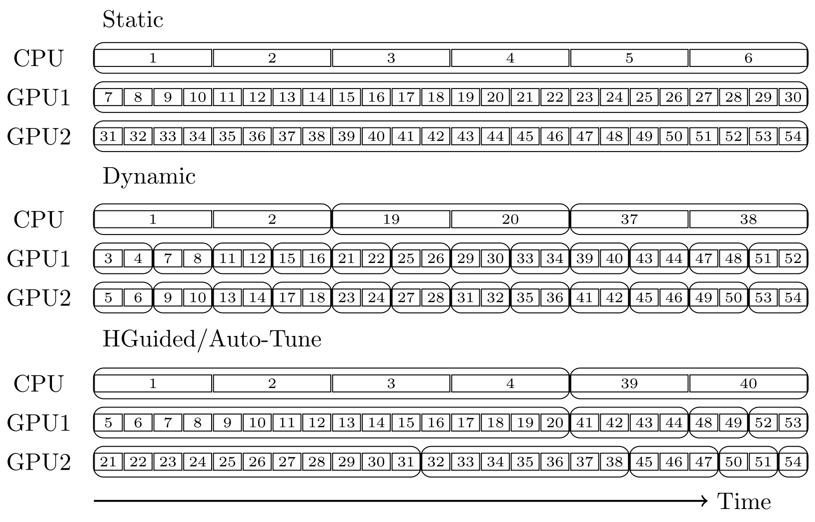


Fig. 1. Depiction of how the four algorithms perform the data division among three devices. The work groups assigned to each device, identified by numbers, are joined in packages shown as larger rounded boxes. Note that the execution time of work groups in the CPU is four times larger than in the GPUs.

together with the data-directionality clauses *in* and *out*, guides the data transfer between the devices and the host CPU, so the programmer perceives a single unified address space.

However, OmpSs does not support the execution of a single kernel instance in several devices. The extension proposed in this article modifies the Nanos++ runtime system so that it can automatically divide a kernel into sub-kernels and manage the different memory address spaces. In order to make the co-execution efficient, four load balancing algorithms have been implemented to suit the behavior of different applications.

3. Load balancing algorithms

The behavior of the algorithms is illustrated in Fig. 1. It shows the ideal case in which in the execution of a regular application all devices finish simultaneously, thus achieving perfect load balance.

3.1. Static algorithm

This algorithm works before the kernel starts its execution by dividing the dataset in as many *packages* as devices are in the system. The division relies on knowing the computing power of the devices in advance. Then the execution time of each device can be equalized by proportionally dividing the dataset among the devices. As a consequence, there is no idle time in any device, which would signify a waste of resources. The idea of assigning a single package to each device is depicted in Fig. 1.

A formal description of the algorithm can be made considering a heterogeneous system with n devices. Each device i has *computational power* P_i, which is defined as the amount of work that a device can complete per time unit, including the communication overhead. This value depends on the architecture of the device, but also on the application that is being run. These powers are input parameters of the algorithm and can be extracted by a simple profiled execution.

The application will execute a kernel over W work-items, grouped in G work-groups of fixed size $L_s = \frac{W}{G}$. Since the work-groups do not communicate among themselves, it makes sense to distribute the workload taking the work-group as the atomic unit. Each device i will have an execution time of T_i. Then the execution time of the heterogeneous system will be that of the last device to finish its work, or $T_H = max_{i=1}^{n} T_i$. Also, since the whole system is capable of executing W work-items in T_H, it follows that its total computational power of the heterogeneous system is $P_H = \frac{W}{T_H}$. Note that it also can be computed as the sum of the individual powers of the devices.

$$P_H = \frac{W}{T_H} = \sum_{i=1}^{n} P_i$$

The goal of the Static algorithm is to determine the number of work-groups to assign each device, so that all the devices finish their work at the same time. This means finding a tuple $\{\alpha_1, \ldots \alpha_n\}$, where α_i is the number of work-groups assigned to the device i, such that:

$$T_H = T_1 = \cdots = T_n \Leftrightarrow \frac{L_s \alpha_1}{P_1} = \cdots = \frac{L_s \alpha_n}{P_n}$$

This set of equations can be generalized and solved as follows:

$$T_H = \frac{L_s \alpha_i}{P_i} \Leftrightarrow \alpha_i = \frac{T_H P_i}{L_s} = \frac{T_H P_i G}{W} = \frac{P_i G}{\sum_{i=1}^{n} P_i}$$

Since α_i is the number of work-groups, its value must be an integer. For this reason, the expression used by the algorithm is:

$$\alpha_i = \left\lfloor \frac{P_i G}{\sum_{i=1}^{n} P_i} \right\rfloor$$

If there is not an exact solution with integers then $\sum_{i=1}^{n} \alpha_i < G$. In this case, the remaining work-groups are assigned to the most powerful device.

The advantage of the Static algorithm is that it minimizes the number of synchronization points. This makes it perform well when facing regular loads with known computing powers that are stable throughout the dataset. However, it is not adaptable, so its performance might not be as good with irregular loads.

3.2. Dynamic algorithm

Some applications do not present a constant load during their executions. To adapt to their irregularities, the dynamic algorithm divides the dataset into small packages of equal size. The number of packages is well above the number of devices in the heterogeneous system. During the execution of the kernel, a master thread in the host is in charge of assigning packages to the different devices, following the next strategy:

1. The master splits the G work-groups in packages, each with the package size specified by the user. This number must be

a multiple of the work-group size. If the number of work-items is not divisible by the package size, the last package will be smaller

2. The master launches one package on each device, including the host itself if it is desired.
3. The master waits for the completion of any package.
4. When device *i* completes the execution of a package:
   (a) The device returns the partial results corresponding to the processed package.
   (b) The master stores the partial results.
   (c) If there are outstanding packages, a new one is launched on device *i*.
   (d) If all the devices are idle and there are no more packages, the master jumps to step 5.
   (e) The master returns to step 3.
5. The master ends when all the packages have been processed and the results have been received.

This behavior is illustrated in Fig. 1. The dataset is divided in small, fixed size packages and the devices process them achieving equal execution time. As a consequence, this algorithm adapts to the irregular behavior of some applications. However, each completed package represents a synchronization point between the device and the host, where data is exchanged and a new package is launched. This overhead has a noticeable impact on performance. The Dynamic algorithm takes the size of the packages as a parameter.

3.3. HGuided algorithm

The two above algorithms are well known approaches to the problem of load balancing in general. But none satisfy three key aspects. First, take into account the heterogeneity of the system. Second, control the overhead of the synchronization. And third, give reasonable performance with regular and irregular applications. Thus a new load balancing algorithm method called *HGuided* was proposed, which is based on the *Guided* method from OpenMP.

The main difference between the HGuided and the Dynamic algorithms is the size and quantity of the packets. In Dynamic, the size of the packets is constant, while in HGuided they vary throughout the execution and between the devices. As execution progresses, the size of the packets decreases with the remaining workload. This size is weighted with the relative computational capacity of each device. This way the less powerful devices (CPUs in this case) run smaller packets than they would in a homogeneous system, and the more powerful devices run larger packets. The package size for device *i* is calculated as follows:

$$package\_size_H = \left\lfloor \frac{G_r}{kN} \cdot \frac{P_i}{\sum_{j=1}^{N} P_j} \right\rfloor$$

Note that the first term gives diminishing size of the packages, as a function of the number of pending work-groups G_r, the number of devices N and the constant k. The latter is introduced due to the unpredictable behavior of the irregular applications. It limits the maximum package size and, in the experimental evaluation of Section 5, was empirically fixed to 2. The second term adjusts the package size with the ratio of the computing capacity of the device P_i to the total capacity of the system.

On the other hand, in the dynamic algorithm, the programmer sets the number of packages for each execution. However, in the HGuided, since the size of the packets depends on the device. Therefore, the number of packages will vary according to the order in which the packets are assigned to the devices. This can differ greatly between runs and especially in irregular applications.

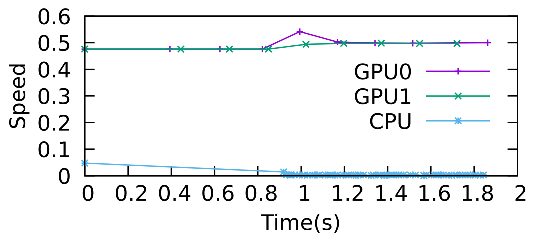


Fig. 2. Evolution of the computing power per device.

Therefore, this algorithm reduces the number of synchronization points and the corresponding overhead, compared to the Dynamic. Fig. 1 shows how the size of the packages is large at the beginning of the execution, and decreases towards the end.

3.4. Auto-Tune algorithm

The HGuided algorithm strikes a balance between adaptiveness and overheads, which makes it a good all-around solution that adequately distributes the workload for both regular and irregular applications. However, it still requires two parameters to be provided by the programmer: the computing power and the minimum package size. These have a key impact on performance and are dependent on both the application to be executed and the system itself. Moreover, the HGuided algorithm is quite sensitive to these parameters, so choosing an adequate value for them is sometimes a demanding task that requires a thorough experimental analysis. The sensitivity of the HGuided algorithm to its parameters is further analyzed in Section 5.3.

In addition, determining the minimum package size parameter is complicated, especially for GPUs, because it is essential to do a sweep to obtain a value that gives good results. The computing capability is easier to evaluate. It only requires obtaining the response times in each device independently and calculating the capacities.

The *Auto-Tune* algorithm is an evolution of the previous algorithm that achieves near optimal performance for both regular and irregular loads without the hassle of parameters. It uses the same formula to calculate the package size, but uses nominal parameter values that are adjusted at runtime and handles the minimum package size differently depending on the device that each package will be sent to.

The computing power for the first package launched at each device is calculated using the theoretical GFLOPs of the hardware. These can be obtained at the installation of OmpSs either by querying the available devices or by running a simple compute intensive benchmark. For the successive packages, the power is updated taking into account the computing speed displayed by each device. This is calculated as the average number of work-items processed per second for the last three packages launched to each device. By using the average speed of the last packages, a gradual adaptiveness is attained that keeps the algorithm resistant to bursts of irregularity that would not be representative of the actual speed for the next packages. Fig. 2 depicts the evolution of the computing power during the execution of one of the applications used for experimentation. The nominal computing powers are used at the beginning of the execution until all the devices have finished at least one package. Then, the computing powers are updated at runtime. In the figure, the nominal power for the GPU was higher than the actual one for the application. Note that the use of the nominal powers for the initial packages does not disturb the load balancing, as all the devices are kept busy and do not delay the completion of the benchmark.

Package size also has an influence on the computing speed of throughput based architectures, such as GPUs. Consequently, package size must be kept relatively high to prevent an inefficient use of the hardware and overheads. However, this is also a potential source for imbalance. If the computing power of the devices differs greatly, a high minimum package size that reduces overheads is likely to be too big for slow devices, namely, CPUs, which would cause delays. To prevent this, the Auto-Tune HGuided algorithm uses different minimum values for CPUs and GPUs. The value selected for the CPU is one work-group per CPU core, so no hardware is left unused and imbalance is avoided. This is because the CPU is not a throughput device, so its computing speed is usually much less sensitive to package size than the GPUs. Moreover, CPUs are often the least powerful device of the system, so using a small minimum package size with them will improve the load balancing. Two values are considered for the GPU minimum package size. First, the equations implemented in the CUDA Occupancy Calculator are used to obtain the minimum number of work-groups that will achieve maximum occupancy for the current kernel and GPU. The CUDA Occupancy Calculator is part of the CUDA Toolkit since version 4.1. This value is a lower bound for the minimum package size, but might be too low if the application launches a large amount of work-items, producing too many packages and high overheads. To prevent this, the number of work-items is also analyzed and the final minimum package size is set to the maximum between the value obtained by the Occupancy Calculator and 5% of the work-items. This percentage has been experimentally set to keep the number of packages low and avoid performance degradation in the GPU.

These enhancements give forth an algorithm with improved adaptiveness, that delivers comparable performance to the HGuided approach for a fraction of the effort. It completely eliminates the need to provide any parameter and saves a great deal of pre-processing time per application and system, as will be seen in Section 5.3.

4. Implementation

As stated before, the OmpSs infrastructure relies on the combination of two components: Mercurium, which is a source-to-source compiler, and Nanos++, which is a runtime capable of managing tasks, their data and the *Task Dependence Graph (TDG)* they generate. As a first approach, the new load balancing algorithms have been implemented focusing on making the changes as self-contained as possible and minimizing the impacts on the OmpSs specification, Mercurium and the rest of Nanos++. As a result, neither directives nor clauses have been added to Mercurium. Nanos++ implements a set of different schedulers that deal with the management of the tasks submitted to the runtime. To offer the work distribution strategies for a single OpenCL task presented in the previous section, a new scheduler has been implemented as a Nanos++ plugin, which has been called `maat`. The parameters of the algorithms are the following:

- The device computing powers for Static and HGuided.
- The package size for Dynamic.
- The minimum package size for HGuided.

To avoid altering the OmpSs specification, the selected algorithm and its parameters are set through environment variables, which is the normal way to specify the scheduler in Nanos++.

Fig. 3 represents the outline of an OmpSs implementation of the Binomial benchmark used later in the experimentation. It shows how a call to a function defined as a task is followed by a wait. The header of that function, which is shown in Fig. 4, indicates that the task must be run in an OpenCL device, as well as its launch parameters, input and output data. Fig. 5 displays the environment variables that need to be set to run the task with each of the four algorithms presented in Section 3. As shown, the selection of the `auto-tune` algorithm eliminates the need of specifying any other load balancing related parameter.

Despite the efforts made to minimize the impact on Mercurium, a minor change was unavoidable. The original implementation did not make OpenCL kernel configuration parameters available to Nanos++. This information is necessary for the operation of the plugin, as it defines the amount of work that will be performed. Nanos++ work descriptors do not hold this information either. Consequently, a new Mercurium work descriptor creation function has been implemented, which behaves like the original but including these parameters.

When a work descriptor is submitted, the new scheduler manages its division in as many work descriptors as the selected algorithm and parameters require. These work descriptors are considered as children of the one submitted, and represent an aggregate workload equivalent to that of their parent. For the Static and Dynamic algorithms, in which the number and size of the packages are known when the launch of the workload is made, all the work descriptors are created at the submission of their parent. They are stored in the scheduler and adequately returned when a thread is idle, receptive to another task. In the case of the HGuided and Auto-Tune algorithms, the packages have varying sizes that depend on the prior execution and the device that will run them. As a consequence, the children work descriptors will be created when required by an idle thread, considering the device it manages and the execution.

Each of the children work descriptors is identical to its parent except in two key aspects. First, they have different OpenCL parameters, namely *offset* and *global_work_size*, defining the workload of the package they represent. There is no constraint on the number of dimensions of the OpenCL data-set of the parent task, as the work division is always performed along the first dimension. Second, the output data is just a portion of that of its parent, which is conveniently offset so the results are written adequately. This is represented by an independent *CopyData* object, holding the start address and size that the package will have to work on. As a result, coherence problems are avoided in the OmpSs directory. Apart from the aforementioned details, data transfer relies on the methods used by standard OmpSs. To perform the correspondence between work descriptors and output data, an assumption is made: each OpenCL work-item will produce the result for the position of the output buffers indexed by its identifier. This may seem a strong requirement, but it is met by most kernels widely used in the industry and research. Input data is replicated in the memory of all the devices, as there is no way to predict the parts that will be read by each of the work-items. This might appear as an important source of overhead, but the experimental results of Section 5 indicate otherwise, as good performances are obtained.

The creation of the children work descriptors is performed by a modified version of the *duplicateWD* function that does this extra work. This function is also responsible for making the OpenCL parameters of the divided work descriptors available to the Mercurium code, which will trigger the actual kernel launches.

Once the submission of the original work descriptor is completed, the *done* function is called. This is a Nanos++ function that is used to signal the completion of a work descriptor. It also waits for the completion of the children of the calling work descriptor. In this way, no task dependent on the divided one will be run until all the children resulting from the work distribution are completed, so the dependencies of the task graph are maintained.

5. Evaluation

This section begins with a description of the system and the benchmarks used in the experiments, as well as definitions of the metrics used in the evaluation. Additionally experimental results are showed and analyzed.

```
//Initializations
binomial_options(NUM_STEPS, SAMPLES,
                 randArray, output);
#pragma omp taskwait
//Free resources
```

Fig. 3. Basic outline of an OmpSs application.

```
#pragma omp target device(opencl) copy_deps  \\
        ndrange(1,samples*(numSteps+1), \\
                numSteps+1)
#pragma omp task in([samples]randArray)  \\
                 out([samples]output)
__kernel void binomial_options(int numSteps,
         int samples, const __global float4*
         randArray, __global float4* output);
```

Fig. 4. Header file for the task.

```
# Static load balancing
NX_SCHEDULE=maat
NX_ALGORITHM=static
NX_GPU_POWER=34.0

# Dynamic load balancing
NX_SCHEDULE=maat
NX_ALGORITHM=dynamic
NX_DYN_PACKAGE_SIZE=409600

# HGuided load balancing
NX_SCHEDULE=maat
NX_ALGORITHM=hguided
NX_GPU_POWER=34.0
NX_MIN_PACKAGE_SIZE=115200

# Auto-Tune load balancing
NX_SCHEDULE=maat
NX_ALGORITHM=auto-tune
```

Fig. 5. Environment variables to use standard OmpSs and the different load balancing algorithms.

5.1. System set-up

The test machine has two processor chips and two GPUs and 16 GBs of DDR3 memory. The chips are Intel Xeon E5-2620, with six cores that can run two threads each at 2.0 GHz. They are connected via QPI, which allows OpenCL to detect them as a single device. Thus, any reference to the CPU considers both processors. The GPUs are NVIDIA Kepler K20m with 13 SIMD lanes and 2496 cores and

Table 1
Maximum achievable speedup per application.

Application	NBody	Krist	Binomial	Perlin	SpMV	RAP
Max. Speedup	2.61	2.2	2.03	2,04	2.05	2,16

5 GBytes of VRAM each. These are connected to the system using independent PCI 2.0 slots. The experiments build upon a baseline system which uses a single GPU but consider the static energy of all the devices, regardless of if they are contributing work or not. This accounts for the fact that many current HPC systems have several accelerators which, if left unused, are a potential source of inefficiency.

Six applications have been chosen for the experimentation. Three of them: *NBody*, *Krist* and *Perlin* are part of the OmpSs examples offered by BSC, and the other three: *Binomial*, *Sparse Matrix and Vector product (SpMV)* and *Rap* have been specifically adapted to OmpSs from existing OpenCL applications. The first four (NBody, Krist, Binomial and Perlin) are regular, meaning that all the work-groups represent a similar amount of work. On the contrary, SpMV and Rap are irregular, which implies that each work-group represents a different amount of work. The parameters associated to each of the load balancing algorithms have been set to maximize performance. The computing power for a device/application pair has been obtained as the relative performance of the device, with respect to that of the fastest device for the application.

Perlin implements an algorithm that generates noise pixels to improve the realism of moving graphics. Krist is used on crystallography to find the exact shape of a molecule using Röntgen diffraction on single crystals or powders. Rap is an implementation of the Resource Allocation Problem. It has a certain pattern in its irregularity, because each successive package represents an amount of work larger than the previous.

The evaluation of the performance of the benchmarks is done through their response time. This includes the time required by the communication between host and the devices, comprising input data and result transfer, as well as the execution time of the kernel itself. The benchmarks are executed in two scenarios, the *heterogeneous system*, taking advantage of the GPUs and CPU, and the *baseline*, that only uses one GPU. Note that in both instances, the same version of the program is run, as there is no need to modify the source or recompile, only set environment variables.

Based on these response times, two metrics are analyzed. The first is the speedup for each benchmark when comparing the baseline and the heterogeneous system response times. Note that, for the employed benchmarks, the CPU is much less powerful than the GPUs, then the maximum achievable speedup using the three devices is not 3, but a fraction over 2 which depends on the computing power of the CPU for the application. The speedup for each application using a perfectly balanced work distribution is shown in Table 1. These values give an idea of the advantage of using the complete system. They were derived from the response time T_i of each device as shown in Eq. (1).

$$S_{max} = \frac{1}{max_{i=1}^{n}\{T_i\}} \sum_{i=1}^{n} T_i \tag{1}$$

The second metric is the load balancing efficiency, obtained by dividing the reached speedup by the maximum speedup, shown in Table 1. The obtained value ranges between 0 and 1 giving an idea of the usage of the heterogeneous system. Efficiencies close to 1 indicate that the best usage of the system is being made. The measured values do not reach this ideal because of the communication and synchronization times between the host and the devices.

5.2. Energy measurement

To evaluate the energy efficiency of the system it is necessary to take into account the power drawn by each device. Modern computing devices include *Performance Management Units (PMU)* that allow applications to measure and control the power consumption. However, the power measured is associated to the device and not the kernel or process in execution. Together with the fact that it is impractical to add measurement code to all the test applications, this led to the development of a power monitoring tool named *Sauna*. It takes a program as its parameter, and is able to configure the PMUs of the different devices in the system, run the program while performing periodic power measurements.

This tool required an unexpected amount of thought for its development. Since it had to monitor several PMUs, it had to adapt to the particularities of each one while giving consistent and homogeneous output data. For instance, each device has a different way to access its PMUs. Recent versions of the Linux kernel provides access to the *Running Average Power Limit (RAPL)* registers [30] of the Intel processors, which provide accumulative energy readings. On contrast, NVIDIA provides a library to access their PMUs. But this *NVIDIA Management Library (NVML)* [26] gives instant power measurements.

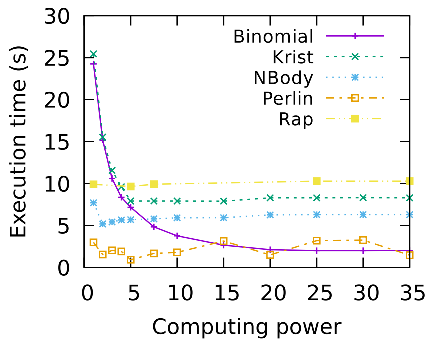
During the development of Sauna, it was observed that these energy or power readings have an impact on the kernel or process execution. Then, finding an adequate sampling period is an important task. To strike a balance between the overhead that was observed in the GPUs with high sampling rates and the accuracy loss that is inherent of lower ones, it was decided to use 45 ms as the sampling period. The performance and the energy consumption can be combined in a single metric representing the energy efficiency of the system. This paper uses the Energy Delay Product (EDP) [5] for this purpose.

5.3. Parameter sensitivity

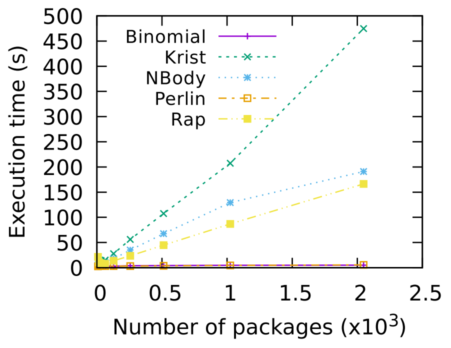
As explained in Section 3, the Static, Dynamic and HGuided algorithms require different parameters for their operation. These have to be provided by the programmer and are one of the key factors for a successful load balancing. However, determining the most adequate values for a workload is not trivial, as they may differ greatly between applications and device configurations. Consequently, the selection of parameters is often a work intensive process, usually based on experimentation.

The importance of adequately choosing the parameter values is illustrated in Fig. 6, which displays the execution time for the applications when varying the parameters for each of the algorithms. Note that for the HGuided algorithm, when one of the parameters is modified, the other is set to the identified optimal value. As shown in the figure, for every of the parameters, the applications show very different behaviors, ranging from near insensitivity to delivering greatly degraded performance, sometimes even lacking a clear relation with the parameter value, as is for example the case of Rap for the minimum package size. Moreover, the applications are not affected equally by the parameters. For example, Binomial is highly sensitive to the computing power in the Static algorithm and moderately sensitive to almost insensitive to the rest of parameters, while Rap behaves just the opposite: it is insensitive to the Static computing power and tremendously sensitive to the other parameters.

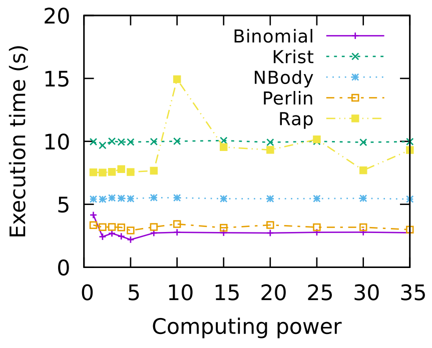
Considering these results, it is obvious that, in order to achieve an accurate load balancing, an experimental tuning of the algorithm parameters is often a must. The Auto-Tune algorithm frees the programmer from this burden by automatically adjusting the parameters, matching and even surpassing the performance of the HGuided.



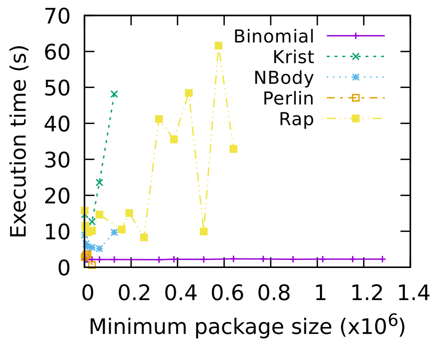
(a) Execution time with different computing powers for the Static algorithm.



(b) Execution time with different numbers of packages for the Dynamic algorithm.



(c) Execution time with different computing powers for the HGuided algorithm.



(d) Execution time with different minimum package sizes for the HGuided algorithm.

Fig. 6. Parameter sensitivity analysis.

5.4. *Experimental results*

The experiments presented in this section have been developed with the optimal values for the parameters required by each algorithm, obtained in the previous section. This implies that the results for the Static, Dynamic and HGuided algorithms are the best that can be achieved, but require a great effort to tune the parameters.

Fig. 7 shows the speedup obtained for each application calculated with respect to their execution time using the baseline system, as was explained in Section 5.1. This section also showed that the maximum achievable speedup depends on the application. These values, presented in Table 1, are shown in the graph as horizontal lines above each benchmark. Additionally, the geometric mean is shown, which includes both four regular benchmarks and two irregular ones.

From the results of the geometric mean it can be seen that the best result is obtained by the Auto-Tune algorithm, closely followed by the Static, the HGuided and finally the Dynamic. Furthermore, it should be emphasized that the Auto-Tune algorithm is much easier to use, because it does not require finding optimal values for any parameter.

A detailed analysis of the speedups reveals that the Static algorithm is the best option for regular applications. This is because they require no adaptivity, so they benefit from the minimum overhead introduced by the Static algorithm. However, except in the case of Perlin, which is very sensitive to overheads as can be seen in the results for all the algorithms but the Static, the Auto-Tune algorithm achieves very similar results with less configuration effort. The other two algorithms achieve good results, but suffer from a problem that reduces performance. If one of the last packages is assigned to the slowest device it is likely to delay the execution of the whole application. This problem could be avoided by increasing the number of packages, but in that case overheads come into play, which also degrade performance. The HGuided algorithm due to its very nature, partially solves this issue.

For irregular applications, the best results are obtained by Auto-Tune and HGuided algorithms. Their adaptive behavior favors load balancing in these applications, where the workload of each work-group is completely unknown and unpredictable. On the other hand, the reduction in synchronization points reduces the runtime overhead, which is inherent to this type of algorithm. This is the reason why the HGuided and Auto-Tune algorithms deliver equal or better performance than the simpler Dynamic algorithm, as they introduce less overhead. Finally, the Static algorithm fails to balance the load because it cannot cope with the unpredictability of these applications.

The load balancing efficiency gives an idea of how well a load is balanced. A value of one represents that all the devices have been working all the time, thus achieving the maximum speedup. In Fig. 8 the geometric mean efficiencies show that the best result is achieved by Auto-Tune with an efficiency around 0.85. In addition, there is at least one load balancing algorithm for every application that achieves an efficiency over 0.9 or even as high as 0.98, reached by Binomial and Perlin with the Static. This is true even for the irregular applications, in which obtaining a balanced work distribution is significantly harder.

Nowadays, performance is not the only figure of merit used to evaluate computing systems. Their energy consumption and efficiency are also very important. Fig. 9 gives an idea of the energy saving the whole heterogeneous system brings, compared to the baseline system. The latter only uses one GPU while the other devices are idle and still consuming. This would be the case of a current HPC system, in which failing to use all the available

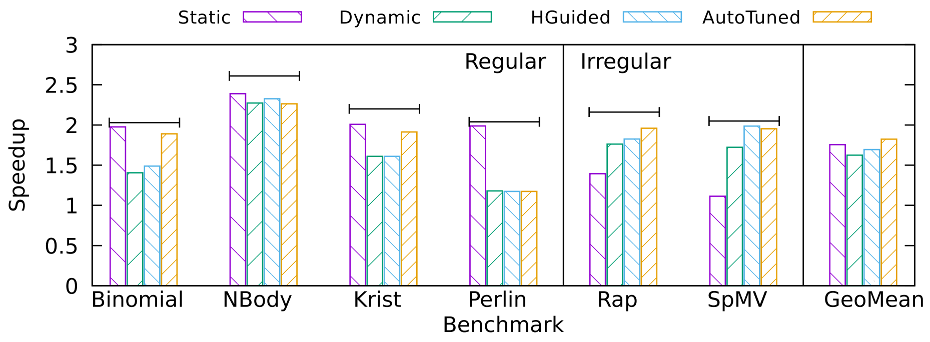


Fig. 7. Speedup per application.

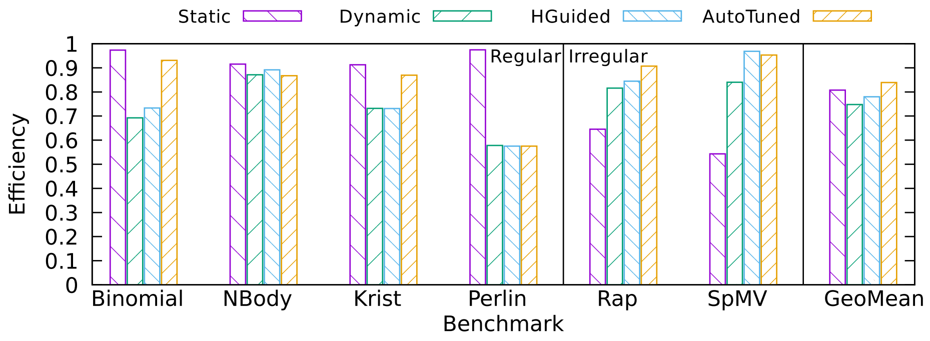


Fig. 8. Efficiency of the heterogeneous system.

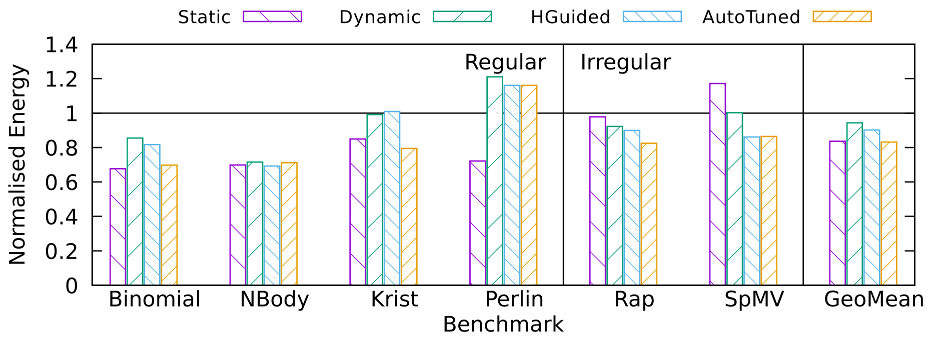


Fig. 9. Normalized energy consumption per application.

resources may represent an energy waste. Therefore, the Figure shows for each benchmark the energy consumption of each algorithm normalized to the baseline consumption, meaning that less is better.

The values of the geometric mean indicate that the algorithms that consume less energy are Static and Auto-Tune, with a saving of almost 20% compared to the baseline. Regarding the individual benchmarks, it is always possible to find an algorithm where the normalized energy is less than one. Moreover, all the algorithms reduce consumption, despite using the whole system. The use of more devices necessarily increases the instantaneous power at any time. But, since the total execution time is reduced, the total energy consumption is also less. Furthermore, since idle devices still consume energy, making all devices contribute work is beneficial.

The analysis of the algorithms shows a strong correlation between performance and energy saving. Consequently, the best algorithm for regular applications is also the Static, with an average saving of 26.5%. However, for irregular applications, it wastes 7.4% of energy. On the other hand, the Auto-Tune gives an average energy saving of 16%.

Regarding the results of concrete benchmarks, it is interesting to comment Krist. The highest energy saving in this benchmark is provided by Auto-Tune, although it is not the best in performance. There are only two particular benchmarks where the use of the whole system employs more energy than the baseline. These are Perlin with Dynamic, Hguided and Auto-Tune, and SpMV with Static. This is because, in these cases, the gain in performance is too small and cannot compensate for the increased power consumption involved in using the complete system.

Another interesting metric is the energy efficiency, which combines performance with consumption. With the dual goal of low energy and fast execution in mind, the *Energy Delay Product (EDP)* is the product of the consumed energy and the execution time of the application. Fig. 10 shows the EDP of the algorithms normalized to the EDP of the baseline.

Since the EDP is a combination of the two above metrics, the previous results are further corroborated. Therefore Auto-Tune also achieves the best energy efficiency results on geometric mean, followed by Static, Hguided and Dynamic. Attending to the individual algorithms, their relative advantages are also maintained.

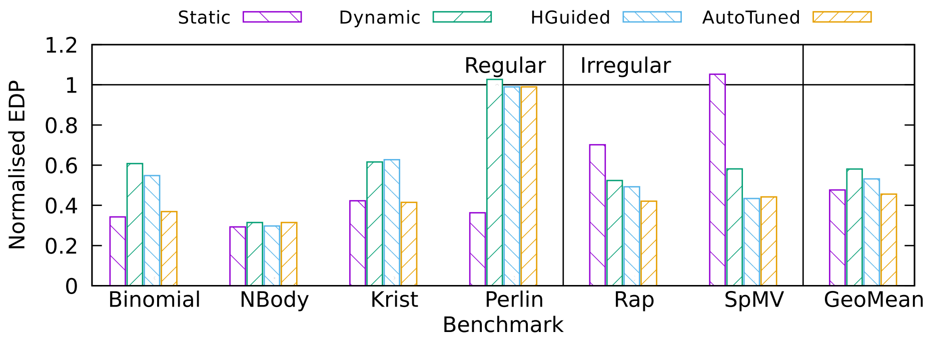


Fig. 10. Normalized EDP per application.

Although the Static algorithm on regular applications shows a significant reduction of the EDP of 65%, the same is not true on irregular ones, reducing only 12.4%. In contrast, the Auto-Tune is more reliable, as it achieves a similar reduction on both kinds of applications; 48% on regular and 57% on irregular.

6. Related work

Heterogeneity has taken computing platforms by storm, ranging from HPC systems to hand-held devices. The reason for this is their outstanding performance and energy efficiency. However, making the most of heterogeneous systems also poses new challenges. The extra computing power also involves new decisions on how to use all the available hardware, which currently have to be made by the programmer without much help from the programming frameworks and runtimes. The keys to make programming easy again are system abstraction, so the heterogeneous devices are handled transparently, and load balancing, so the resources are adequately used. Nevertheless, related as they are, these problems are often addressed separately.

The strategies for co-execution presented in this paper are built upon the system abstractions already offered by OmpSs [8,31] and focus particularly on the load balancing problem. However, some related system abstraction research works are worth mentioning. Such is the case of DistCL [6], which is a framework that enables the distribution of a kernel over a GPU cluster by using user defined meta-functions. These are callbacks that represent the memory access pattern of each devices, so the programmer can instruct the framework on how to distribute the data and reduce data transfers. In [13], the GPUs of the system are abstracted and the addresses accessed by each device are computed using sampling run on the host of some select work-items. The authors of [18] attain abstraction via kernel transformations and a static kernel analysis that determines whether the data need to be replicated or can be split.

To the load balancing problem alone, there are two main approaches found in the literature: *static* and *dynamic*, which in turn can be adaptive or not.

Regarding static methods, Lee et al. [17] propose the automatic modification of OpenCL code that executes on a single device, so the load is balanced among several. De la Lama et al. [16] propose a library that implements static load balancing by encapsulating standard OpenCL calls. The work presented in [15] uses machine learning techniques to come up with an offline model that predicts an ideal static load partitioning. However, this model does not consider irregularity. Similarly, Zhong et al. [40] use performance models to identify an ideal static work distribution. In [18] the focus is on the static distribution of a single kernel execution to the available devices via code modifications. Qilin [19] is a training-based work distribution method that proposes to balance the load using a database containing execution-time data for all the programs the system has executed and a linear regression model. This technique is only useful in systems that run the same applications frequently.

In the dynamic approach [9,10] propose different techniques and runtimes. However, these focus on task distribution and not on the co-execution of a single data parallel kernel. The work of [23] deals with the dynamic distribution of TBB parallel_for loops, adapting block size at each step to improve balancing. FluidicCL [27] does focus on co-execution but for systems with a CPU and a GPU. SnuCL [14] also tackles data parallelism, but is mostly centered on the distribution of the load among different nodes using an OpenCL-like library.

Kaleem's et al. proposal in [12] and Boyer's et al. in [3] propose adaptive methods that use the execution time of the first packages to distribute the remaining load. However, they focus on a CPU/GPU scenario and do not scale well to configurations with more devices. Navarro et al. [23] propose a dynamic, adaptive algorithm for TBB that uses a fixed package size for the GPU and a variable one for the CPU to try to achieve good balancing. This work was extended in [36], proposing an adaptive package size for the GPU too. This is also based on using small initial packages to identify a package size that obtains near optimal performance.

In the traditional research area of dynamic loop scheduling, [11] presents Factoring, an algorithm with variable chunk sizes that addresses the problem of irregularity, referred to as iteration variance. However, it does not consider heterogeneity. HDSS [2] is a more recent work that proposes a load balancing algorithm that dynamically learns the computational power of each processor during an adaptive phase and then schedules the remainder of the workload using a weighted self-scheduling scheme during the completion phase. However, this algorithm assumes that the packages launched in the initial phase are representative of the whole load, which might not be true for irregular kernels. Besides, package size decreases linearly during the completion phase, which may produce unnecessary overheads as substantiated in this paper.

Scogland et al. [32] propose several work distribution schemes that fit different accelerated OpenMP computing patterns. However, they do not propose a single solution to the load balancing problem. The library presented in [28] also implements several load balancing algorithms and proposes the HGuided, which adapts to irregularity and considers heterogeneity. This library is also used in Xeon Phi base systems in [25]. However, it requires certain parameters from the programmer that may not be easy to obtain and uses linearly decreasing packages that might incur overheads.

Some papers propose algorithms to distribute the workload between CPU and GPU taking performance and power into account. For instance, GreenGPU dynamically distributes work to GPU and CPU, minimizing the energy wasted on idling and waiting for the slower device [20]. To maximize energy savings while allowing marginal performance degradation, it dynamically throttles the frequencies of CPU, GPU and memory, based on their utilizations. Wang and Ren [37] propose a power-efficient load distribution method for single applications on CPU–GPU systems. The method coordinates inter-processor work distribution and frequency scaling to minimize energy consumption under a length constraint. SPARTA is a throughput-aware runtime task allocator for Heterogeneous Many Core platforms [7]. It analyzes tasks at runtime and uses the obtained information to schedule the next tasks maximizing energy-efficiency.

With respect to the problem of transparently managing a heterogeneous system, the authors of [35] propose a framework for OpenCL that enables the transparent use of distributed GPUs. In this same vein, Cabezas et al. [4] present an interesting architecture-supported take on efficient, transparent data distribution among several GPUs. Nevertheless, this works overlook load balancing, which is essential when trying to make the most of several heterogeneous devices. Maestro [33] implements concepts related to the abstraction of the system, but the load balancing algorithm it proposes requires training.

You [38], Zhong [39] and Ashwin [1] do address both load balancing while abstracting the underlying system and data movement. Nevertheless, their focus is on task-parallelism instead of on the co-execution of a single data-parallel kernel. Kim et al. [13] approach the problem by implementing an OpenCL framework that provides the programmer with a view of a single device by transparently managing the memory of the devices. Their approach is based on a Static load balancing strategy, so it cannot adapt to irregularity. Besides, they only consider systems with several identical GPUs, lacking the adaptability that OmpSs offers.

There are also some contributions that focus on scheduling and load balancing for OmpSs tasks. For instance, the scheduler presented in [29] is closer to the idea of co-execution. It holds several implementations of a task, targeted for different devices, that will be run iteratively. The scheduler stores the execution time of each implementation, so it can take load balancing decisions on what implementation is best to run next. However, the programmer is responsible for mapping the computation on several iterative tasks, which may not be an easy and natural approach for the application at hand.

7. Conclusions and future work

This paper presents a new scheduler of the OmpSs programming model that allows to efficiently co-execute a single OpenCL kernel instance using all the devices in a heterogeneous system. The scheduler has been conceived so that it is fully transparent to the programmer, who only needs to select the algorithm and set its parameters through environment variables.

Similarly to OpenMP, the scheduler provides different load balancing algorithms. These include the classic Static and Dynamic algorithms, as well as a version of the Guided, called HGuided, that takes into account the heterogeneity of the system. Achieving good results with these algorithms required the tuning of several parameters. Therefore, this paper also presents a novel load balancing algorithm called Auto-Tune, which is capable of automatically determining suitable values for internal parameters through the execution.

Judging by the results of all the experiments presented in this paper, two conclusions can be reached. First, the use of kernel co-execution on modern heterogeneous systems is very important, as the executed benchmarks showed a significant improvement in performance, energy consumption and efficiency. Second, although there are some particular cases in which the Static algorithm outperforms the Auto-Tune algorithm, the latter achieves excellent results without a tedious and time-consuming phase of parameter optimization, which would be necessary for each new benchmark or system.

According to our experimental results, Auto-Tune is capable of taking advantage of the whole heterogeneous system, with an average efficiency of 0.85. Since all the compute devices of the machine are used, the execution time is reduced and consequently, an average energy saving of 16% has been observed. The combination of these two improvements gives a reduction of the EDP close to 50%.

The future of this extension will see compatibility with new devices, like Intel Xeon Phi, FPGAs or integrated GPUs. From the OmpSs perspective, a modification of the pragma specification would allow the programmer to select different algorithms or parameters for different kernels of the same application. It would be interesting to extend the evaluation to different systems and device configurations.

Acknowledgments

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