

# Experiences with task-based programming using cluster nodes as OpenMP devices

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## Abstract

Programming a distributed system, such as a cluster, requires extended use of low-level communication libraries and can often become cumbersome and error prone for the average developer. In this work, we consider each node of a cluster as a separate OpenMP device, able to run code with OpenMP directives in parallel. We make use of the OpenMP device model to provide an easy and intuitive way to program available cluster nodes. Based on that, we examine modifications that were necessary to make existing task-based applications able to exploit such an infrastructure. Finally, we evaluate the performance of the system and conclude that one can gain significant speedup, as long as the application tasks do not produce excessive communication overheads.

## 1 Introduction

High-performance scientific applications always require computationally powerful systems to execute on. On one hand, parallel systems with shared memory architectures are relatively easy to program, for example by using the directive based approach of OpenMP, but do not scale well. On the other hand, distributed-memory systems scale well, but programming them requires low-level libraries that are usually cumbersome and error prone for the average developer to use. As it is natural, a lot of effort has been devoted to combine these approaches and get the best of both worlds; scalable distributed systems that also are easy and intuitive to program.

Early attempts tried to implement transparent execution of OpenMP programs on clusters using software Distributed Shared Memory (sDSM) libraries. The role of an sDSM library is to keep memory consistent between separate nodes, as it would be on a shared memory system. This means that whenever a global (shared) variable is modified, all nodes must at some point be notified about the change, in order for the execution of the program to proceed correctly. A prominent system to take this approach was Intel's

Cluster OpenMP. But, even with the help of compiler analysis to keep as many variables as possible private to each node, these solutions did not always perform well in real world applications, as shown in [1], because of memory sharing overheads and the need for global synchronization.

The fourth release of the OpenMP specification offered support for coprocessors and accelerators using the new *target* directive. The programmer still has to manually define which parts of his code should run on the accelerator (or any similar "device") and which variables need to be sent over, but the implementation takes care of the low-level details concerning how to communicate and exchange data with the devices.

In this work we examine the applicability of the OpenMP device model as a means of harnessing the nodes of a cluster by an OpenMP-only application, especially for applications whose code contains task-based computations. In particular:

- We implement a new device module in the OMPi OpenMP compiler which presents cluster nodes as separate OpenMP devices. The devices can execute code through the OpenMP *target* directive, with transparent handling of code and data transfers.
- We elaborate on how to restructure existing task-based OpenMP applications so as to exploit such devices. That way, a computation can be distributed quite easily among the nodes of a cluster.

The rest of this paper is organized as follows. Section 2 discusses related work, while Section 3 provides the necessary background on OpenMP and more specifically its device model. Section 4 thoroughly describes the design and implementation of our new module, that is able to offload code to nodes of a cluster. Section 5 presents application cases and reports on their performance. Finally, Section 6 concludes the paper.

## 2 Related Work

Devices were added to OpenMP in V4.0 of its specifications [2]. While OpenMP specifications have recently reached V5.1, device support remains rather limited; there exist relatively few compilers supporting relatively few device types. The Intel Xeon Phi co-processor can be programmed under several models and OpenMP was one of the first to be ported. Barker and Bowden [3] measure and analyze the performance of two scientific applications ported to Xeon Phi, using the offload and native execution programming models.

GPUs are arguably the devices that receive most of the OpenMP offloading support. The authors in [4] discuss their efforts implementing the OpenMP 4.5 specification into the Clang/LLVM project to support NVIDIA GPUs. The recent versions of the GCC compiler [5] support offloading code to Intel Xeon Phi accelerators and NVIDIA GPUs using the OpenMP programming model.

Envisaging remote computers as possible OpenMP devices is not a new idea, but the related literature is quite limited. Our approach is similar to the work by Jacob et al. [6]. The authors elaborate mainly on the conceptual model while giving limited insights on their implementation and its functionality within the LLVM compiler; a bioinformatics, loop-based application is then used to demonstrate the potential of the proposed model, experimenting with the loop schedules. In our work we give a detailed description of the device implementation which is available in the context of the open-source OMPi compiler, and with node heterogeneity in mind. Moreover, we utilize the new device to (re)write task-based OpenMP applications and report on our experiences.

Instead of treating cluster nodes as separate devices, Yviquel and Araújo [7] propose a method to handle an entire cloud infrastructure as a single device using map-reduce Spark nodes and remote communication management. Finally, in [8] the authors utilize the device model of OpenMP as an annotation mechanism to denote possibly migratable computation among cluster nodes. The authors do not aim to use cluster nodes as OpenMP devices; they rather extend their previous work [9] which targets hybrid MPI+OpenMP applications with the aim of providing work-stealing functionality across MPI rank boundaries at the application level.

## 3 The OpenMP Device Model

Since the introduction of OpenMP V4.0, offloading portions of code to devices (typically GPUs and other accelerators) is made possible by using the *target* directive. Statements that are inside the block that follows the *target* directive get executed at the specified device (or at the default device if none is specified) and not at the main processor (also called *the host*); such blocks are called *kernels*. Other

Listing 1: Array addition at a device.

```
1 double a[1024];
2 double b[1024];
3 double c[1024];
4 int size = 1024;
5
6 void add_at_device(double *a, double *b,
7                   double *c, int size)
8 {
9     #pragma omp target map(to:a[0:size],b[0:
10    size],size) map(from: c[0:size])
11     {
12         int i;
13         #pragma omp parallel for
14         for (i = 0; i < size; i++)
15             c[i] = a[i] + b[i];
16     }
```

OpenMP directives and parallel regions are allowed to exist inside kernels. The *map* clause of the directive allows the programmer to define a map between variables of the host system and the device, meaning that data can be transferred to and from a device with one of the following four ways:

- If the map type is *to* the value of the variable gets copied from the host to the device before the execution of the block. This is useful for initializing data.
- If the map type is *from* the value of the variable gets copied from the device to the host after the execution of the block. This is useful for getting the results back.
- If the map type is *tofrom* we achieve the combination of the previous two options. This is useful if we have data whose value will be used and modified and we need the final value.
- If the map type is *alloc* a data mapping between the host and the device is created, but no data is transferred. This is useful for auxiliary data that does not have a predefined initial value, neither we need its final value.

To make the above points more clear, Listing 1 gives a simple example. The code performs array addition at a device. At first, variables *a*, *b*, *c* and *size* exist only in host's memory. When the *target* directive gets executed, memory is allocated at the device for the arrays *a*, *b* and *c* of *size* elements each, starting at position 0, because of the `[0:size]` section. Memory for the variable *size* is also allocated. The values of the arrays *a* and *b*, as well as the variable *size* which are mapped with type *to* get copied from host's to device's memory.

Subsequently, the array addition gets offloaded and executed in parallel at the device, because of the *parallel for* OpenMP directive. That way one can fully utilize the device's processing cores. When the calculation is completed,

the elements of array `c` which is mapped with type *from* get copied from the device's to the host's memory. It is useful to remember that data transfers are required given that the host and the device have different memory spaces; in cases where the device shares memory with the host, some or all data may be accessed through shared memory, possibly avoiding copies and transfers.

## 4 The `mpinode` Device

The OMPI compiler [10] is a lightweight OpenMP C infrastructure, composed of a source-to-source translator and a flexible, modular runtime system. OMPI is an open source project and targets general-purpose SMPs and multicore platforms. It provides a large portion of the OpenMP V4.5 functionalities, including full support for device constructs.

The compiler uses *outlining* to move the code of each target block into a separate function, called a *kernel function*. The final executable file consists of all user's code as well as all kernel functions.

Regarding devices, the runtime system of OMPI is organized as a collection of *modules* each one implementing support for a particular device class; multiple devices (of the same type) may be served by one module. Modules consist of two parts: the host part and the device part. The former enables the host (main CPU) to access any of the available module's devices through a fixed interface and is loaded on demand as a plugin (shared library). The device part provides OpenMP and other runtime support within the device, for the offloaded code.

To support a new device in OMPI, one has to create a new module that implements OMPI's interface for communication with devices. For our purposes here, we created the *mpinode* module; an *mpinode* device is simply a computer with MPI installed. In order to exploit cluster nodes, the user is required to create a simple configuration file. All nodes appear in this file and every line contains the name or IP address of a single node, followed optionally by an integer. Each of the listed nodes is considered as a separate device where the user can offload code to. Appending an integer, say *D*, is equivalent to having the node appear in *D* different lines in the configuration file. In such a case, *D* devices will be started at that node. The user may find this characteristic useful to better utilize a node's resources, if the offloaded codes do not generate enough parallelism.

### 4.1 Operation

When a program starts, the initial process running on the host calls `MPI_spawn()` to spawn a process on each node specified in the configuration file. Each process then calls `MPI_Intercomm_merge()` to merge the communicators, so that the process running on the host gets assigned MPI rank 0. When MPI creates a new process, it just copies the executable to the new node, so processes check their

MPI rank to determine if they run at the host or at a device. The process that runs at the host is the only one that executes the program, including all user's code; all the other processes first perform some necessary initialization and then enter a loop waiting for commands from the host.

Communication is achieved by using the MPI library. Two devices cannot communicate with each other directly (that is without mediation of the host); this is an OpenMP restriction. Devices wait for a command from the host, execute it and then return to their waiting state. Here are the types of commands remote *mpinode* processes listen for:

- Allocate or deallocate memory at the device.
- Transfer data to or from the device.
- Execute a kernel function.
- Stop a device when the application exits.

A command might be composed of a sequence of MPI messages; for example, the host sends a message asking for the value of a variable and the device replies with a message that contains it. The device must always know the type of the command it is asked to execute, so the host always includes it in the first message.

Because the processes operating at remote nodes have been spawned as replicas of the initial host process, they contain all kernel functions. Consequently, there is no need to actually transfer the kernel code at offloading time. However, the host cannot instruct an *mpinode* device to execute a kernel function by just sending the memory address of the function, since different machines may store program code and data at different virtual addresses, even if they run the same executable file. To solve this problem, every node constructs a *kerneltable* structure, which maps each kernel function to a unique integer. Internally, the kerneltable is a dynamically allocated array whose every element consists of the name of a kernel function and a pointer to its code. At offload time, the host searches its kerneltable for the given kernel function name and simply sends the array index that corresponds to the function to the device. The device uses that index on its own kerneltable to retrieve a pointer (in its own address space) to the function it should execute. The kerneltable is populated at program start, before executing any user code, by sequentially inserting each kernel function's name and pointer. This occurs independently at each cluster node and because every node runs the same executable, functions are entered in each kerneltable in the exact same order; as a result, each function is mapped to the same unique integer across all nodes.

### 4.2 Data Handling

As per OpenMP specifications, for each *target* region the host must maintain mappings of all host variables with the corresponding device variables, so that transfers can be initiated to/from the host address space form/to the device

space. In the case of cluster nodes, it may be difficult or even impossible for the host to know the exact virtual address where the corresponding (remote) variables will be stored at. For such scenarios OMPI introduces a level of indirection, which we call a *mediary address*: Instead of mapping a host address to a device address, it maps a host address to an abstract intermediary address. Transfers to/from the device utilize the intermediary addresses; the device is then responsible to translate intermediary addresses to its own memory space addresses. It is up to the module implementor to decide what exactly the intermediary address represents. With this mechanism, the host is able to create mappings even if the corresponding variables have not yet been allocated on the remote device.

When handling a *target* directive, the host creates a struct in which it places the intermediary address for each variable that is accessed in the *target* block. Then, before commanding kernel execution, it sends the struct to the appropriate device which uses it to extract the actual device address of each variable. These device addresses will subsequently be used during kernel execution. For the *mpinode* module, intermediary addresses are simple integers and are implemented as follows:

- Each device keeps a dynamic array which maintains all memory allocation requests. When the host asks for a new allocation (e.g. requesting space for a corresponding variable), the first unused array element is found and the requested amount of memory is allocated on the device with a `calloc()` call, storing its address at this array element. Unused elements contain the `NULL` address. The address stored at the array element is the actual device address of the corresponding variable, while the array index of the element is used as the intermediary address of the variable; the latter is used when communicating with the host.
- The host is not technically required to keep such an array; it could ask the device for the next available intermediary address, but that would require further message exchanges and thus cause additional overheads. Consequently, as an optimization, the host maintains a mirror of the above array for each device. Of course, the host does not need to allocate any memory, it only needs to remember which elements are in use. Accordingly, to allocate memory for a new variable on a device, the host first finds the first unused array element and marks it with the special (and arbitrary) value of `0x999`. Then it notifies the device to proceed with allocating memory, as described above. This way the host knows in advance the intermediary address that the device will use. Unused elements again contain the `NULL` address.

All nodes place the addresses of global variables (such as variables declared within *declare target* regions) in their arrays at the beginning of the execution and in the same

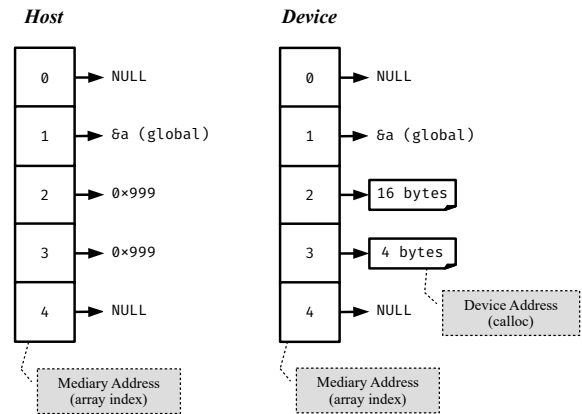


Figure 1: Example of a intermediary address array at the host (left) and the device (right).

order, before executing any user code. Global variables and their addresses are retrieved from OMPI's internal data structures.

Figure 1 shows an example of a intermediary address array at the host (on the left) and a device (on the right). We suppose that the example program only has one global variable named `a`. Also, the host has asked the device to allocate memory two times; the first one for an array of 16 bytes and the second for a variable of 4 bytes. Naturally, when a *target* block is done executing and any required data transfers have taken place, allocated variables are freed from the device's intermediary address array and their positions are marked as unused at both the host and the device array.

For the best possible performance, one may employ OpenMP *target* directives inside *parallel* directives, meaning that different threads at the host can communicate with different devices simultaneously. That requires the *mpinode* module to be thread safe; this in turn requires the MPI implementation to be thread safe. Furthermore, many communication operations require two phases; first the host sends data to the device and then calls `MPI_Recv()` to get the response. If two threads at host communicate with the same device simultaneously, one might end up receiving the other's data. If they communicate with different devices, the problem does not occur because the host checks the source rank of the device process when calling `MPI_Recv()`. We could use the *tag* parameter of `MPI_Recv()` calls to solve the problem, but we decided to have it available for future use. Instead, every time we want to use MPI functions, we check if we are inside a parallel region and, if so, we lock a *mutex* dedicated to the device we want to use. When the host inserts or removes entries from the intermediary address array, it also uses the same *mutex* to prevent data races at the array.

### 4.3 The Device Part

As mentioned previously, the device part of an OMPi module is responsible for providing OpenMP facilities and runtime support to an executing kernel. In common cases it has the form of a static library that gets linked with the offloaded kernel, implementing the required services. In our case, the device part of the *mpinode* module is effectively empty. The reason is that the executable that runs across the cluster already contains the host's runtime library linked in. That is, a fully fledged OpenMP runtime is already present in the executable and is utilized as-is to offer complete OpenMP facilities to any kernel executing on any remote node.

## 5 Evaluation

### 5.1 Methodology

Once the *mpinode* module is implemented, every node in a cluster is accessible as a separate OpenMP device. The proposed system represents a straightforward way to exploit multiple cluster nodes without resorting to complex message passing. It can be used to easily (sometimes trivially) offload any kind of code to cluster nodes using only OpenMP directives. Conceptually, a block of code accompanied by the required data are sent for execution to other CPUs; this aligns perfectly with the tasking model of OpenMP and opens up the possibility of programming a whole cluster by only using OpenMP tasks.

To assess the programmability as well as evaluate the performance of such an approach, we use selected applications from the Barcelona OpenMP Task Suite (BOTS) [11], and more specifically alignment, fib and sparselu. All of them use OpenMP tasks to perform parallel calculations on a shared-memory machine. We modified them by adding *target* directives to execute portions of the calculations at different nodes. Apart from BOTS, we also parallelized a sequential Mandelbrot set application using OpenMP tasks and our *mpinode* module.

The general idea when modifying existing applications is to find computationally intensive parts of the code that do not require a lot of data for their calculations and wrap them inside *target* directives. Since a node of a typical cluster consists of more than one CPUs and many processing cores, it is beneficial if the *target* block contains additional *parallel for* or *task* directives, so the node's resources are better utilized. Alternatively, the same node can be treated as multiple different devices by including its IP address multiple times in the configuration file.

In some cases, for example when having nested *task* directives, all one has to do is rename the external *task* into *target*. But, most of the time, it requires more work; one needs to create as many *target* regions as there are devices (for example by splitting the iterations of a loop) and specify which variables and which array sections each device

Listing 2: Array addition at multiple devices.

```
1 double a[1024];
2 double b[1024];
3 double c[1024];
4 int ndevices = 8;
5
6 #define START device*size
7 #define END   device*size+size
8
9 void add_multidev(double *a, double *b,
10                 double *c, int ndevices)
11 {
12     int size = 1024 / ndevices;
13     int device;
14
15     #pragma omp master
16     for (device = 0; device < ndevices; device
17         ++)
18     {
19         #pragma omp target device(device+1)
20             firstprivate(size,device) map(to:a[
21                 START:END],b[START:END]) map(from:c[
22                 START:END]) nowait
23     {
24         #pragma omp parallel for
25         for (int i = START; i < END; i++)
26             c[i] = a[i] + b[i];
27     }
28 }
```

will use. In any case, for the average user the process is faster, easier and less error prone than having to restructure a program to utilize MPI.

As a concrete example, in Listing 2 we revisit Listing 1, which performed array addition at a single device; the new program utilizes 8 devices to perform the addition. We assume that the `add_multidev` function is called from a parallel region. The loop in line 16 creates a *target* region for each of the 8 devices. Since we want this operation to be performed once, we use a *master* directive in line 15.

The *target* directive at line 18 utilizes the device specified by the *device* clause. Note that we start from device 1, since device 0 is the host machine. As explained in Section 3, arrays *a* and *b*, as well as variables *size* and *device* are copied to the device, while array *c* is copied back to the host when execution reaches line 23. In contrast to Listing 1 where the entire arrays are copied, only the required 128 elements of each array are copied per device, using appropriate array sections. The *nowait* clause indicates that the host thread will not wait until the offloaded region is completed. To fully utilize the cores within each device, we create a *parallel for* region in line 20.

### 5.2 System Specifications

All experimentation took place at a commodity cluster we had direct access to. The cluster consists of 16 nodes with

2 CPUs each (dual core AMD Opteron @ 2193MHz) and 12GB memory. Nodes communicate through a humble Gbit Ethernet network. Each node runs Ubuntu 16.04.4 LTS with Linux 4.4.0 and uses GCC 5.4.0 and OpenMPI 3.0.2. To evaluate the performance of our module, we used 2 to 12 nodes, depending on the benchmark. We measured the speedup we gained compared to execution in one machine (where we executed the original version of each benchmark using only a single random node of the cluster).

For an unbiased comparison, we used GCC as the reference OpenMP implementation instead of the original OpenMP. However, the problem we faced is that the tasking implementation in the available version of GCC performs inexplicably poorly in some cases, resulting in high execution times and false superlinear speedups for our module. Because of such cases, we also report speedups with respect to using our module on a single machine; this also serves to show how *mpinode* performance scales with the utilization of more nodes. We executed each experiment 10 times and averaged the results. We note that we did not alter the way BOTS measure and report performance results, i.e. they measure the execution time (wall clock time) of the parallel section of the program, not the time required for the initialization or the finalization. Thus, the reported times do not include the (one-shot) delays of starting and stopping MPI processes on remote nodes.

### 5.3 Protein Alignment

The alignment program performs protein alignment. From a programmer’s perspective, it produces a one dimensional array, where each element can be calculated independently of all the others. For its calculation, many arithmetic operations with auxiliary arrays and variables are required, which do not change during the execution of the program, and thus can be sent once at each device (at the beginning of the execution). We modified this program so that if we have  $n$  devices and the output array has  $m$  elements, each device calculates  $m/n$  elements. We were careful to send to devices only the portions of the arrays that were absolutely necessary to calculate their assigned work, in order to limit the communications as much as possible.

As a result, we achieve parallelization at two levels. First, the host separates the work into equal parts and simultaneously asks the devices to calculate their part (using a *target* directive). Secondly, each device executes its kernel function in parallel by creating multiple threads to calculate the result it was assigned (using a *task* directive).

Figures 2 and 3 show the execution time of the alignment program, when given as input the files `prot20.aa` (that produces an output array of 400 elements) and `prot100.aa` (that produces an output array of 10000 elements), respectively. The execution time when using only OpenMP *tasks*, that uses 4 threads in one node, is shown with dashed lines. In all other cases, the total number of threads we use is 4 multiplied by the number of devices.

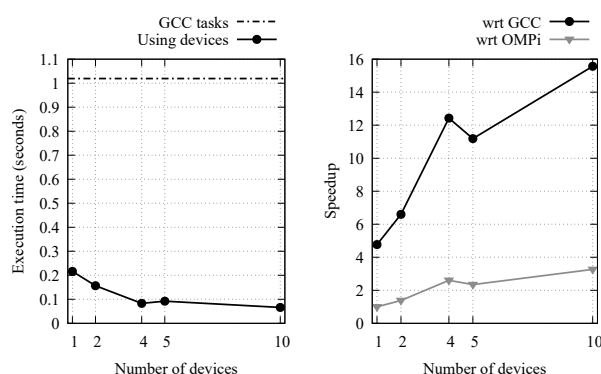


Figure 2: Plot of execution time and speedup of alignment program for input size 20.

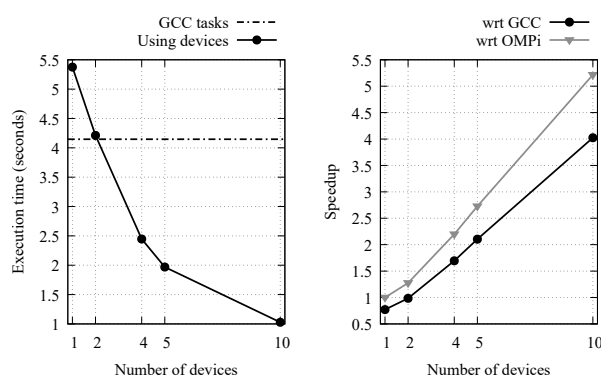


Figure 3: Plot of execution time and speedup of alignment program for input size 100.

The communication overhead is small, since the amount of communicated data is small, but each device has quite a lot of work to do. Furthermore, the biggest part of communication takes place once, at the beginning of the program. For the `prot20.aa` file, GCC was problematic, exhibiting consistently high execution times. As a result, the speedup we achieve reaches the unreal value of 15.57. For the larger problem of `prot100.aa` our system scales linearly with the number of nodes.

### 5.4 Mandelbrot Set

The mandelbrot program creates a Mandelbrot fractal image (which is a two dimensional array) with the provided dimensions. The calculation of the value of each pixel requires only the position  $(x, y)$  of the pixel. We parallelized a sequential version of the program such that each device constructs a strip (a number of adjacent rows) of the image, so the only information a device needs is the position and the size of the strip it has to construct. We also added a *parallel for* directive so that each device can calculate its rows in parallel. When a strip is completed, it needs to be sent back to the host, and that can require a significant amount of communication, depending on the image dimensions.

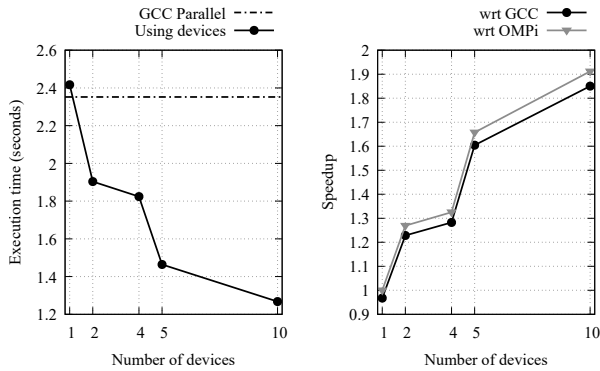


Figure 4: Plot of execution time and speedup of mandelbrot program for an image with size 2600x2600 pixels.

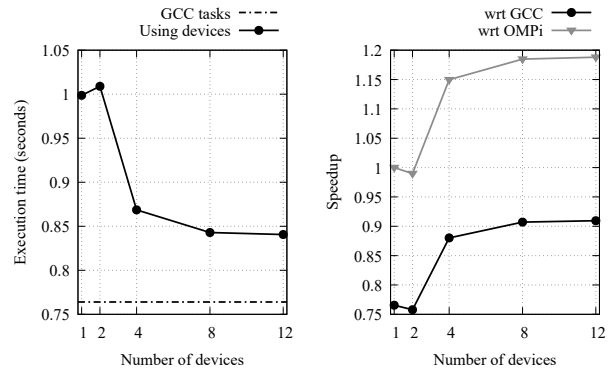


Figure 6: Plot of execution time and speedup of fib program for the number 35.

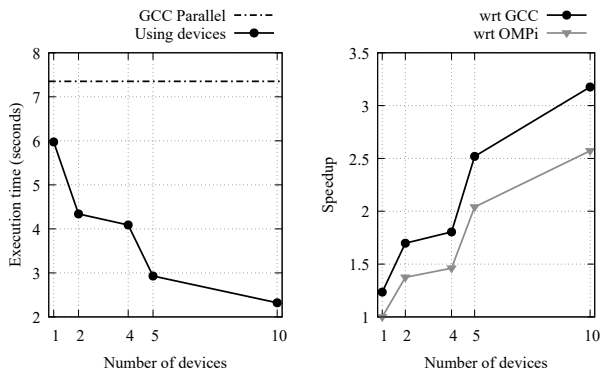


Figure 5: Plot of execution time and speedup of mandelbrot program for an image with size 4600x4600 pixels.

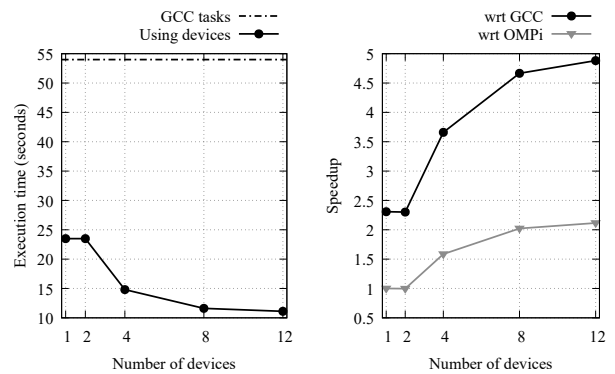


Figure 7: Plot of execution time and speedup of fib program for the number 45.

Figures 4 and 5 show the execution time of the mandelbrot program, when generating an image of 2600x2600 and 4600x4600 pixels, respectively. In the former case, the speedup we gain is 1.85, while in the latter it is 3.18, with respect to GCC. We observe that when doubling the image dimensions, the work load increases significantly (the sequential execution time triples), but the amount of communications does not increase as dramatically, thus resulting in increased speedup.

## 5.5 Fibonacci

The fib program calculates a given Fibonacci number by performing only recursive calls. Because of the recursion we needed to adapt our strategy. The limitation is that OpenMP only allows communication between the host and a device, not between two devices, meaning that a device cannot send work to another one. Thus, if the root task is offloaded to a cluster node, all subsequent recursive tasks will have to be executed in the same node. To solve this problem, we let the host execute the first recursive calls. When the recursion unwinds to the point where the number of recursive calls (i.e. generated tasks) is equal to the number of available devices, the host can offload the tasks to

the devices and wait for their results. Notice, however, that there is an inherent imbalance here as the generated tasks do not contain the same amount of computations. Each device employs multiple threads to execute the tasks that were present in the original version of the program in parallel. The only communication required for the program is that the host must send a single integer to each device (that represents the Fibonacci number the device has to compute) and receive a single integer from each device (that represents the computed result).

Figure 6 shows the execution time of the fib program, for the calculation of Fibonacci number 35. We observe that the calculation of this number at our cluster requires less than one second. The speedup we gain compared to using only *tasks* at one node reaches 0.91 in the best case; this implies that there is not enough work to keep nodes busy, and using *tasks* in a single node gives better performance. On the other hand, the calculation of 45th Fibonacci number produces deeper recursions and a huge number of tasks, requiring significantly more computation time and producing less imbalance. As a result, as shown in Figure 7, the addition of more devices seems to produce small but not negligible speedups; the large value of 4.88 with respect to GCC is due to its suboptimal tasking performance.

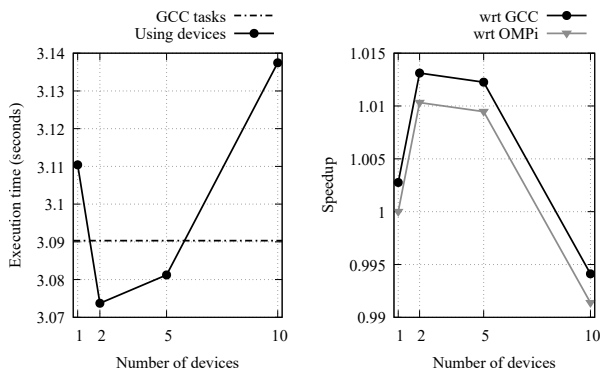


Figure 8: Plot of execution time and speedup of sparselu program for an array of size 2500x10000.

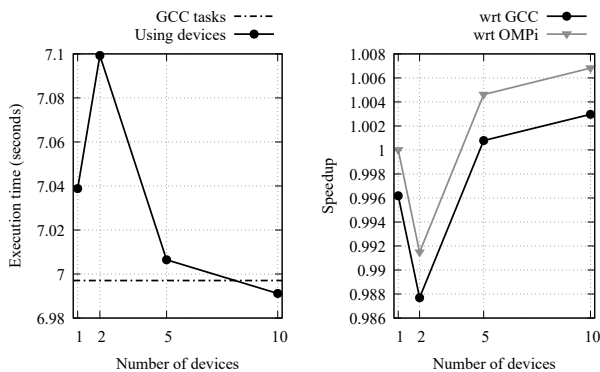


Figure 9: Plot of execution time and speedup of sparselu program for an array of size 3600x14400.

## 5.6 Sparse LU

Finally, the sparselu program performs LU analysis on a sparse array, whose dimensions are given by the user. We modified that program so that each device processes only a portion of the array in parallel, using the *task* blocks of the original version of the program. As a result, the host separates the array into smaller ones of equal size and sends a sub-array to each device. Furthermore, when the calculation is completed, the resulting sub-arrays must be sent back to host. That implies large communication volumes that get worse as the array dimensions increase; in essence, the whole array must be transferred two times.

Figures 8 and 9 show the execution time of the sparselu program, for arrays of size 2500x10000 and 3600x14400, respectively. Because of the serious communication delays, we essentially gain no speedups. Using cluster offloading for applications that require a lot of communication, does not seem a very beneficial idea in general.

## 6 Conclusion

In this paper we present the design and implementation of a module that treats each node in a cluster as a separate

OpenMP device, capable of running parallel code that contains arbitrary OpenMP constructs. Without resorting to message passing, this facility represents a very simple way for an OpenMP application to extract additional computational power from a cluster, when available, essentially for free.

We present the implementation details of our module in the context of the OMPi compiler, including the way we use MPI to handle the communication between the host and the devices and the way we assign mediary addresses to variables that need to be transferred to devices.

Finally we provide our experiences with utilizing the new module as a means to deploy task-based OpenMP applications onto clusters. We analyze the programming techniques employed when modifying existing OpenMP applications to use *target* constructs and kernel functions. Our experimentation shows that with a very small effort one can gain significant speedups, as long as the application does not require extensive communication between the host and the devices and each device has enough computations to perform.

The need for intensive communication between the host and the devices is the main source of performance degradation. We currently analyze and profile the communication patterns, in order to find ways to reduce the overheads, or avoid them altogether, if possible. Furthermore, we plan to extend OpenMP directives to provide a more user friendly way of partitioning arrays and sharing them among devices. This way, it may also be possible to use MPI collective communications to optimize communication between host and devices.

The *mpinode* module is available in the official repository of OMPi (<http://paragroup.cse.uoi.gr/wpsite/software/ompi/>).

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