How Algorithm Definition Language (ADL) Improves the Performance of SmartGridSolve Applications

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Abstract

In this paper, we study the importance of languages for the specification of algorithms in high performance Grid computing. We present one such language, the Algorithm Definition Language (ADL), designed and implemented for the use in conjunction with SmartGridSolve. We demonstrate that the use of this type of language can significantly improve the performance of Grid applications. We discuss how ADL can be used to improve the execution of some typical algorithms that use conditional statements, iterative computations and adaptive methods. We present experimental results demonstrating significant performance gains due to the use of ADL.

1. Introduction

Scientific numerical simulations typically need large amount of computational resources during their execution. Many scientific applications use Grid computing because it provides an easy way to gather computational resources, whether local or geographically distributed, that can be pooled together to solve large problems. An application to be executed in a Grid environment needs to logically divide its core algorithm into a group of tasks that can be executed remotely. GridRPC [11] is a standard promoted by the Open Grid Forum that provides a simple remote procedure call (RPC) mechanism to easily execute tasks in a Grid environment. Using the GridRPC API an application programmer can easily specify different tasks to be executed remotely. GridRPC works by individually mapping a task to a single server in the Grid and communicating the data between the client machine and the remote server. This model supports minimisation of the execution time of each individual task of the application rather than the minimisation of the execution time of the whole application. A number of Grid middleware systems are GridRPC compliant including GridSolve [13], Ninf-G [12] and DIET [5].

In order to optimally minimise the total execution time of an application, a Grid middleware would require the full knowledge of all the tasks executed in the application’s algorithm. A task graph, a direct acyclic graph (DAG) structure, can be used to fully represent the algorithm. The task graph specifies the order of tasks execution and their synchronisation (whether they are executed in sequence or in parallel), the data dependencies between tasks, the load of data communication and the task computational volume. This information is essential to choose the best server to execute a task and to minimise the amount of data movement in a Grid.

SmartGridSolve [3] is a Grid middleware that uses task graphs of algorithms to achieve higher performance in scientific applications. SmartGridSolve implements the new SmartGridRPC [2] model that expands the individual task mapping and client-server communication model of GridRPC by implementing server-to-server communication and the mapping of groups of tasks. The collective mapping of tasks, with the possibility to use a fully connected network, permits SmartGridSolve to calculate an optimal mapping solution of an algorithm that can fully exploit the Grid environment.

SmartGridSolve uses the SmartGridRPC API to automatically generate the task graph from the application code. This works by iterating twice through the code that contains the task calls to be mapped collectively. On the first iteration through the code, each task call is discovered but not executed remotely. On the second iteration, after producing the mapping by using the new task graph, the code is normally executed and the task calls are performed according to the newly mapping solution. The automatic construction of the task graph works flawlessly for many regular or static algorithms, i.e. algorithms where the execution is not influenced by the inputs, because the flow of task calls is known at run-time before their execution. Thus, the task graph generated for such an algorithm accurately represents its run-time execution. This permits
SmartGridSolve to obtain an optimal mapping for this kind of algorithm and therefore to obtain better results than GridSolve, as it is in the case of the real-life astrophysical application discussed in [10].

Unfortunately, this approach has the restriction that a representative task graph may not be always automatically generated for every kind of code. The automatic construction of task graphs may not work for irregular or dynamic algorithms, i.e. algorithms where the execution changes depending on the inputs. A typical example is when, in the code, a conditional construct checks a value that cannot be known without executing a remote task call. To apply collective mapping in this case, the application programmer can choose to create task graphs for smaller blocks of code. However, the resulting groups of tasks to be mapped will generate a less optimal execution.

A solution to this problem, which we propose, is to use algorithm specification languages to provide the application programmers with a means that would allow them to use their knowledge of the application to explicitly specify a task graph that best represents the run-time execution of the irregular algorithm. The mapping generated for this task graph can achieve a faster execution time than the single task mapping of GridRPC or the mapping of smaller groups of tasks. In this paper we present one such language: the Algorithm Definition Language (ADL). We discuss how the use of ADL can improve the performance of SmartGridSolve applications. ADL [9] is a new language designed to help an application programmer to easily specify a task graph for all kinds of algorithms.

This paper is outlined as follows. Section 2 presents three example algorithms that model real-life irregular algorithms that are common in many scientific applications. These algorithms are outlined using three trivial applications implemented in GridRPC and SmartGridRPC. In addition, section 2 shows how the automatic task graph generator works and demonstrates its restrictions. Section 3 shows how the application programmer can use ADL to generate representative task graphs for the example algorithms. It presents a brief description of the language syntax and how ADL can be used in conjunction with SmartGridSolve. Section 4 presents results of experiments with the example applications showing that the use of ADL significantly improves their performance. Section 5 focuses on the existing languages that are used to generate task graphs or similar structures for workflow management systems and GridRPC middlewares. Furthermore, this section focus on the conclusion obtained from this work.

2. Irregular Algorithms and their GridRPC & SmartGridRPC implementations

Irregular algorithms, where the flow of task calls change dynamically, are important because they are common in many scientific simulations. In this section, we introduce three trivial examples of irregular algorithms. These examples are models of typical algorithms used to solve real-life problems. For each algorithm, we present its GridRPC and SmartGridRPC implementations. The SmartGridRPC implementations are then used to show the restrictions of the automatic task graph generation method. We also present some programming techniques that help somehow mitigate these restrictions.

The following examples use the GridRPC methods grpc\_call and grpc\_call\_async to execute blocking and asynchronous remote calls respectively. The first argument of both methods is the handler of the task executed, the second is the session ID of the remote call, while the following arguments are the parameters of the task. The code uses the method grpc\_wait\_all to block the execution until any previously issued asynchronous request has completed. The SmartGridRPC examples utilise a new method, grpc\_map. This method is used to define a specific area of code. All the tasks calls contained in this area are mapped as a group of tasks on to a fully connected network. The first parameter of the grpc\_map method allows the application programmer to choose which mapping heuristic to use. The second one indicates the tool that will be used to generate the task graph, while the following parameters depend on the previous choice. SmartGridRPC defines another new function, grpc\_local, which is used in the following examples as well. This API function is used to identify the area of code that contains local computations. The following examples consist of many tasks (T1, T2, ...), where all the parameters are input objects except the last one that is an output object. The same is applied to the functions (F1, F2, ...), which represent local computations. The objects (A, B, ...) used in the examples are all vectors of double precision numbers. All the examples have these characteristics except when indicated differently.

**Iterative Algorithm** An iterative algorithm executes a sequence of computations to approximate a problem solution until the solution reaches a desired accuracy. This algorithm is a general model of so called iterative methods. They are used for solving linear and non-linear algebraic equations that are the base of many numerical simulations.

Table 1 shows the GridRPC implementation of a trivial application that uses an iterative algorithm. At the beginning, two parallel remote T1 task calls are executed. These tasks compute a new solution of the objects A0 and A1 from inputs B0 and B1. Then, the output objects, A0 and A1, are used as inputs of the remote task T2. The output of the latter task, D, is then used as input to a local function F1. The function returns a scalar value E that is compared to a threshold value, tE. When the returned value is lower than the threshold, the algorithm stops.

When the application is executed, the GridSolve mid-
middleware maps each `grpc_call` and `grpc_call_async` functions individually to a server in the Grid environment. Then, the data is communicated from the client computer to the chosen server and the task executed remotely. At the end of the task execution, the data is communicated back to the client.

Table 1. Example of GridRPC implementation of an iterative algorithm

```c
while(E>tE){
    grpc::call_async(T1_hnd,&id1,A0,B0,A0);
    grpc::call_async(T1_hnd,&id2,A1,B1,A1);
    grpc_wait_all();
    grpc::call(T2_hnd,&id3,A0,A1,D);
    F1(D,E);
}
```

Table 2 shows how the SmartGridRPC API can be used in the previous application to map a group of tasks. This example uses the automatic task graph generator to build the task graph. At run-time, when the `grpc_map` method is executed, the code within its parenthesis will be iterated through twice. On the first iteration, both `grpc_call` and `grpc_call_async` calls are discovered but not executed. At the beginning of the second iteration, the task graph and the mapping solution are generated using the task information from the previous discovery. On the second iteration, the task calls are executed through the SmartGridSolve middleware on the respective servers specified by the mapping solution. The block of code defined by `grpc_local` is not executed during the discovery phase, which is done on the first iteration, but only on the execution phase, which is done on the second iteration.

Table 2. Example of SmartGridRPC implementation of an iterative algorithm

```c
while(E>tE){
    grpc::call("ex_map",auto){
        for(i=0;i<nloops;++){
            grpc::call_async(T1_hnd,&id1,A0,B0,A0);
            grpc::call_async(T1_hnd,&id2,A1,B1,A1);
            grpc_wait_all();
            grpc::call(T2_hnd,&id3,A0,A1,D);
            F1(D,E);
        }
    }
}
```

In table 2 it is possible to see that for this example the `grpc_map` method is used inside a while loop. A straightforward SmartGridRPC implementation would be to apply the `grpc_map` to the whole loop, letting the middleware find the optimal mapping for the group of all remote tasks. Unfortunately, the automatic task graph generator will not be able to build a representative task graph for this straightforward implementation because the number of iterative cycles executed is unpredictable during the discovery phase. A solution to this problem is to use the SmartGridRPC function inside the while loop in conjunction with a for loop statement. This implementation prevents the undefined behaviour of the algorithm during the discovery phase. Furthermore, the programmer can choose the number of iterations, `nloops`, to map simultaneously. Although the code in table 2 executes more iterations than the code of table 1 when there is convergence and `nloops` is greater than one, the SmartGridSolve execution of the SmartGridRPC implementation will usually outperform the GridSolve execution of the GridRPC one by virtue of the better mapping.

Conditional Algorithm A common situation in a numerical computation arises when the flow of execution in an algorithm depends on a conditional statement. This situation can happen in many types of algorithms, even in the iterative methods previously discussed. Table 3 shows the GridRPC implementation of a trivial application that uses a conditional algorithm. The peculiarity of this application is that the local function `F1` is used in the conditional statement to choose which data objects will be used by the following task `T3`. If the value returned by this local function is greater than a given threshold, objects `A0` and `A1` will be processed, otherwise it will be objects `B0` and `B1`.

Table 3. Example of GridRPC implementation of a conditional algorithm

```c
if(F1(D)>tE) {
    grpc::call_async(T3_hnd,&id4,C0,A0,A0);
    grpc::call_async(T3_hnd,&id5,C1,A1,A1);
    grpc_wait_all();
}
else {
    grpc::call_async(T3_hnd,&id4,C0,B0,B0);
    grpc::call_async(T3_hnd,&id5,C1,B1,B1);
    grpc_wait_all();
}
```

The ideal task graph, to be used to map this application, would represent the exact run-time execution of the remote tasks. Thus, the ideal location for the `grpc_map` method would be at the beginning of the code to contain all the task calls of the algorithm. As in the case of the previous example, this ideal task graph cannot be generated by the automatic method because the application’s execution is uncertain in the conditional statement. A technique, that allows the application programmers to still avail themselves of the group mapping in SmartGridSolve, is to break the whole code into smaller blocks suitable for the automatic task graph generation as show in table 4. This solution however produces many small groups of tasks. Therefore SmartGridSolve will minimise the execution time of these small groups rather than the whole algorithm, thus producing a less optimal mapping. Additionally, the data objects used between groups instead to be communicated directly.
between servers, they will be communicated through the client machine. Figure 1 shows a possible ideal task graph for this example. This graph illustrates the data dependencies between the tasks executed before and after the conditional statement (diamond node client 5 in the figure).

Table 4. Example of SmartGridRPC implementation of a conditional algorithm

```c
grpc_map("ex_map",auto){
    grpc_call(T1_hnd,&id1,A,B,C);
    grpc_wait_all();
    if(T1(D)>tE)
        grpc_map("ex_map",auto){
            grpc_call(T3_hnd,&id4,C0,C1,A1,A1);
            grpc_wait_all();
        }
    else
        grpc_map("ex_map",auto){
            grpc_call(T3_hnd,&id3,C0,C1,A0,A0);
            grpc_wait_all();
        }
    grpc_wait_all();
}
```

Adaptive Algorithm Typically an algorithm executes its computation on a specific data structure. Some algorithms dynamically change their internal data structure, and consequently their behaviour, depending on the data processed. These algorithms are called adaptive algorithms.

Table 5. Example of GridRPC implementation of an adaptive algorithm

```c
grpc_all(T1_hnd,&id1,A,B,C);
for(int i=0;i<n;i++)
    grpc_all(T5_hnd,&id2,A,B,AS[i],BS[i]);
grpc_wait_all();
```

Table 5 shows the GridRPC implementation of a trivial application that uses an adaptive algorithm. In the first step of this example, the task \( T1 \) calculates the solution \( C \) of the total computational domain. Then, this data together with a threshold value \( t_E \) are passed to the task \( T4 \). Task \( T4 \) checks \( C \) and outputs a vector of areas, \( S \), and the number of such areas, \( n \). The areas in the vector \( S \) represent the location where the solution error is greater than the threshold \( t_E \). In the next step, task \( T5 \) outputs two sub-vectors, \( AS \) and \( BS \). These subvectors are an interpolation, of higher resolution, of the main vectors \( (A, B) \) for each area in \( S \) previously found. The subvectors are then used to calculate a more accurate solution \( (CS) \) through task \( T1 \). This is a trivial example of the AMR (Adaptive Mesh Refinement) method, a real-life example of the adaptive algorithm.

In this example, the outputs of task \( T4 \) not only change the flow of execution of the algorithm but also change the sizes of the objects computed by the following tasks. This is one of the worst case scenarios for the automatic task graph generation. On the discovery phase, the data objects \( n \) and \( S \) are unknown. Therefore, unpredictable will be not only the flow of execution but also the data objects’ sizes. As in the previous example, a solution is to apply `grpc_map` to smaller blocks of code, as shown in table 6.

Table 6. Example of SmartGridRPC implementation of an adaptive algorithm

```c
grpc_map("ex_map",auto){
    grpc_call(T1_hnd,&id1,A,B,C);
    grpc_all(T4_hnd,&id2,C,tE,S,n);
}
for(int i=0;i<n;i++)
    grpc_map("ex_map",auto){
        grpc_all(T1_hnd,&id2,A,B,AS[i],BS[i]);
    }
    grpc_wait_all();
}
```

3. ADL and Task Graph

As shown in section 2, the automatic task graph construction method cannot generate representative task graphs for all the irregular algorithms. Therefore, SmartGridSolve cannot generate the best mapping solution possible for this type of algorithm. We have shown that this problem can be partially solved by mapping smaller code blocks, with some modification of the code of the application (table 2) or without it (tables 4 and 6).

In this paper, we present a comprehensive solution of this problem, which is the use of ADL, the Algorithm Definition Language. This new language and its compiler provide a means to the application programmer to explicitly specify a task graph for all kinds of algorithms. The programmers, with their knowledge of the application’s algorithm, possess the right information to produce a representative task graph for any given group of tasks in the application. The ADL syntax is similar to the C language. The principal programming unit of this language is a module that is used to specify the group of tasks of an individual algorithm. The ADL compiler does not directly produce the task graph from the module but generates the code that is used at run-time to build the task graph. In this section, we show how the application programmer can use ADL to originate a representative task graph for the conditional and adaptive example algorithms.

Conditional Algorithm Table 7 shows the ADL module that describes the algorithm of our example conditional application. An ADL module is composed of a name, a list of parameters and a body. The body is divided in the following sections. The `component` section includes a declaration of the tasks used in the algorithm, such as \( T1, T2 \) and \( T3 \) for the example application. The `IFO` section contains a declaration of data objects. In ADL, the data objects, that
are used in a task and can be moved anywhere on the Grid, are called Identified Flying Objects (IFOs). Their declaration is composed of the type (in upper-case letters to differ from a variable type), the number of dimensions and the list of IFO names. The number of round bracket pairs, located after the type, represent the number of dimensions of an IFO. In the example application, the IFOs A, B, C, D, are vectors of double precision numbers. The sizes of these vectors depend on the value of the parameter size. Finally, the algorithm section describes the flow of execution of the application.

Table 7. ADL module of the conditional algorithm example

| module cndalg(int size, int cndtrue, int cndfalse)|
| 2 component: |
| 3 task "cond.idl" T1,T2,T3; |
| 4 IFOs: |
| 5 DOUBLE(size) A[2],B[2],C[2],D; |
| 6 algorithm: |
| 7 parfor(int i=0;i<2;i++) { |
| 8 T1:(A[i],B[i])-->C[i]); |
| 9 } |
| 10 T2:(C[0],C[1])-->D); |
| 11 client: (D) ->{}; |
| 12 parallel |
| 13 if(cndtrue) |
| 14 parfor(int i=0;i<2;i++) |
| 15 T3:(C[i],A[i])-->A[i]); |
| 16 if(cndfalse) |
| 17 parfor(int i=0;i<2;i++) |
| 18 T3:(C[i],B[i])-->B[i]); |
| 19 } |
| 20 |

Table 7 shows how a task call is described in ADL. A remote call is composed of two parts, divided by a semicolon. The first part is the name of the task called (e.g. T1), followed by a list of parameters needed. The second part is the list of IFOs used as task inputs, e.g. A and B for task T1, followed by an arrow symbol and the list of output IFOs (e.g. C). This task call syntax is made in a way that easily highlights the parameters passed and the IFOs used as inputs and outputs of the task. The parfor construct specifies that the task calls between the iterations of the loop are asynchronous while the task calls inside the same iteration are sequential. The parallel construct indicates that all the included statements are considered asynchronous. One of the main differences between the ADL code and the application code is the use of the keyword client, as a task name, to specify any local execution. For the purpose of task graph generation, ADL does not need to know which local computations will be done and which local data will be used in these computations. The only information needed is which IFOs are used in these computations (but not their values). Thus, in the case of a local computation, ADL requires only the information about the IFOs used as inputs and outputs of this computation. Therefore, in table 7 the client task has only D as an input and no output, and the name of the client task, F1, is not included in the specification.

The straightforward description of the conditional algorithm would be with an if-then-else statement, as it is in the original SmartGridRPC code in table 4. Instead, in the ADL example in table 7, the module contains two conditional statements, in lines 13 and 16, that check the value of the parameters cndtrue and cndfalse. The application programmer, by setting only one of these two values to true, can choose the flow of execution that is most likely to happen. Furthermore, the programmer can choose to generate and use a task graph that contains both branches of the execution by setting the two parameters to be true simultaneously. The parallel construct in line 12 is used to avail this option. Without it, the compiler will consider the two branches as being executed sequentially, one after the other. The setting of different parameters values allows the application programmer to easily choose the most representative task graph from a set of different possible task graphs. Furthermore, the parameters in ADL are not only used to determine the control flow of the algorithm but also to specify the size and the number of IFOs utilised in the module. An IFO cannot change its size after the declaration, consequently all the parameters are considered constant in the ADL language.

Table 8. Example of ADL use in the conditional algorithm application through SmartGridRPC

```
grpc_map("ex_map",ADL,cndalg, *id, *kd,*kd",size,1,1){
grpc_call_async(T1_hnd,in(id1,A0,B0,C0);
grpc_call_async(T1_hnd,in(id2,A1,B1,C1);
    ... if(F1(D)>tE) ...
    else ...
}
```

Table 8 shows how to use the grpc_map method with ADL to build the task graph. The first argument of the function is the same as in the example of table 4. The second argument, instead of the keyword auto, is the keyword ADL. This specifies that the task graph will be built by using the code generated from the ADL module named in the following argument. The next argument is a string that contains the quantity and the type of parameters passed to the module. The format is similar to the printf function call of the C language. The final arguments in the grpc_map method match the parameters of the given ADL module. In table 8, the application programmer has decided that both conditional statements are true. The run-time execution of the grpc_map function is different from the case of the automatic method. The task graph is built and the mapping solution is generated directly when the method is called. Therefore, the code inside the parenthesis block will be iterated only once while the task calls are executed normally on the servers specified in the mapping solution. Thus, the use of the function grpc local is not needed in this situation.
Adaptive Algorithm

The task graph generated from the code of table 8 is illustrated in figure 1. The rectangles in the graph represent remote tasks, the diamonds represent the client computation and the circles represent the IFOs. The incoming arrows of these circles indicate their source, whether it is the client or another remote task and the outgoing arrows indicate their destination. The dotted arrows highlight the order of task calls and if the tasks are executed in sequence or parallel. The values inside the circles and rectangles are respectively the size of an IFO and the computational complexity of a task. These are correlated to the value of the module parameter size passed through the third to last argument of the grpc_map method. One can see that the generated task graph contains the task calls for both possible flows of execution of the conditional statement.

Adaptive Algorithm

Table 9 shows the ADL module that describes the algorithm of our example adaptive application. One can see that the sizes of data objects A, B, C, depend on the parameter size. The parameter n is used to determine the number of areas in vector S that could be generated by the task T4. Furthermore, the value of n is used to set the number of times that task T5 is executed and hence the number of subvectors (AS, BS, CS) that are generated. The parameter subsize is a vector of integers that contains the sizes of each subvector object. Its dimension depends on the value of n.

The application programmer, by setting the values of the three parameters in grpc_map, can directly specify the number of task calls and the sizes of objects in the task graph generated. Table 10 shows the use of the ADL module adaptalg in the modified adaptive SmartGridSolve application. In this case, the application programmer presumes that the remote computation of task T4 produces n = 3 and thus the programmer chooses to generate a task graph with three T5 calls. The size of data objects will be 1000 and the subvectors’ sizes will be 200, 100 and 300. Figure 2 shows the generated task graph.

4. Experimental results

In this section, we compare the execution times, for both conditional and adaptive example algorithms, of the three different implementations: the GridRPC version (tables 3 and 5), the SmartGridRPC with smaller mapping blocks version (tables 4 and 6) and the SmartGridRPC with ADL version (tables 8 and 10). The first implementation is executed through the GridSolve middleware while the last two are executed through the SmartGridSolve middleware. The hardware configuration used in the experiments consists of fives machines: a client and four remote servers. The four servers are heterogeneous however they have similar performance, from 422 to 531 MFlops, and the same size of main memory, 1GB each. The bandwidth of the communication links between servers is 1Gbps. The client machine has a 100Mbs connection to the servers. This represents a common situation where a user wants to use a powerful Grid environment through a relatively slow network connection. In the experiments, we vary the total input data size, n, from 24 to 576 megabytes. Each remote task executed has a logarithmic complexity, O(n × ln n). This complexity, with the slow client-to-server connection, permits the computation

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**Figure 1. The task graph generated from the ADL module of the conditional algorithm**

**Table 9. ADL module of the adaptive algorithm example**

<table>
<thead>
<tr>
<th>module</th>
<th>adaptalg(int n, int size, int subsize[n])</th>
</tr>
</thead>
<tbody>
<tr>
<td>component:</td>
<td>T1,T4,T5;</td>
</tr>
<tr>
<td>task</td>
<td>&quot;adapt.idl&quot;</td>
</tr>
<tr>
<td>IFO:</td>
<td>T1_hnd, &amp;id1, A,B,C;</td>
</tr>
<tr>
<td>DOUBLE(size)</td>
<td>A,B,C;</td>
</tr>
<tr>
<td>DOUBLE(subsize)</td>
<td>AS[n], BS[n], CS[n];</td>
</tr>
<tr>
<td>INTEGER(n)</td>
<td>S;</td>
</tr>
<tr>
<td>algorithm:</td>
<td>T1: (A,B) -&gt; (C);</td>
</tr>
<tr>
<td>T4: (C) -&gt; (S);</td>
<td></td>
</tr>
<tr>
<td>parfor(int i=0;i&lt;n;i++)</td>
<td>T5: (S,A,B) -&gt; (AS[i],BS[i]);</td>
</tr>
<tr>
<td>parfor(int i=0;i&lt;n;i++)</td>
<td>T1: (AS[i],BS[i]) -&gt; (CS[i]);</td>
</tr>
</tbody>
</table>

**Table 10. Example of ADL use in the adaptive algorithm application through SmartGridRPC**

```c
grpc_map("ex_map",ADL,adaptalg,"3,1000,[200,100,300]"){
    grpc_call(T1_hnd,&id1,A,B,C);
    grpc_call(T4_hnd,&id4,C,tE,S,n);
    for(int i=0;i<n;i++){
        grpc_call_async(T5_hnd,&id3,i,S,A,B,AS[i],BS[i]);
        grpc_call_async(T1_hnd,&id4,AS[i],BS[i],CS[i]);
        grpc_wait_all();
    }
}
```
load and the communication load to have an equal impact on the total execution time of the experiments. In the following tables, the symbol $S_p$ stands for speed-up; while $GS_p$ is the abbreviation for GridSolve and $SGS_p$ is the one for SmartGridSolve with smaller mapping blocks.

**Table 11. Experimental results for the conditional algorithm applications**

<table>
<thead>
<tr>
<th>Data Size</th>
<th>GridSolve</th>
<th>SmartGridSolve with smaller blocks</th>
<th>$S_p$ v GS</th>
</tr>
</thead>
<tbody>
<tr>
<td>24MB</td>
<td>24.08s</td>
<td>19.31s</td>
<td>1.25</td>
</tr>
<tr>
<td>48MB</td>
<td>48.30s</td>
<td>40.35s</td>
<td>1.20</td>
</tr>
<tr>
<td>96MB</td>
<td>97.51s</td>
<td>81.00s</td>
<td>1.20</td>
</tr>
<tr>
<td>192MB</td>
<td>195.80s</td>
<td>156.67s</td>
<td>1.25</td>
</tr>
<tr>
<td>384MB</td>
<td>404.31s</td>
<td>317.36s</td>
<td>1.27</td>
</tr>
<tr>
<td>576MB</td>
<td>648.02s</td>
<td>497.31s</td>
<td>1.30</td>
</tr>
</tbody>
</table>

**Table 12. Experimental results for the adaptive algorithm applications**

<table>
<thead>
<tr>
<th>Data Size</th>
<th>GridSolve</th>
<th>SmartGridSolve with smaller blocks</th>
<th>$S_p$ v GS</th>
<th>$S_p$ v SGS</th>
</tr>
</thead>
<tbody>
<tr>
<td>24MB</td>
<td>24.08s</td>
<td>19.31s</td>
<td>1.25</td>
<td>1.20</td>
</tr>
<tr>
<td>48MB</td>
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</tr>
<tr>
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<td>81.00s</td>
<td>1.20</td>
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Table 11 shows the results obtained by the GridSolve and SmartGridSolve executions of the three different implementations of the conditional algorithm. For each individual experiment, the average time is calculated from ten separate executions, where the condition of the conditional statement is set to return true in half of them. In the SmartGridSolve with ADL experiments, the task graph generated by ADL contains both branches of the execution. One can see that the SmartGridSolve implementation, with smaller blocks to map, is faster than the simple GridSolve implementation, showing the speed-up of approximately 1.2. Furthermore, the SmartGridSolve implementation, that uses a representative task graph generated from ADL, outperforms the other two implementations, displaying the speed-up of approximately 1.7 and 1.4 respectively.

The speed-up demonstrated by the SmartGridSolve implementation, with smaller blocks to map, over the GridSolve execution is less than in the previous experiments with the implementations of the conditional algorithm. The reason is that the tasks in the second mapping block of this application (see table 6) are less computationally intensive than the tasks in the first mapping block. The subvectors are smaller than the original vectors. Therefore, the improved SmartGridSolve mapping of the parallel tasks in the second block is limited by the execution time of the tasks in the first block. At the same time, the speed-up obtained by the SmartGridSolve implementation using ADL over the other two implementations is similar to the conditional algorithm experiments. The reason is that use of ADL permits SmartGridSolve to map a larger group of tasks and to minimise
the amount of data moved in the network.

5. Related Work & Conclusion

SmartNetSolve [4], the predecessor of SmartGridSolve, was using an XML file to generate the task graph. The client programmer had to explicitly specify the full task graph for each group of tasks in the program. A similar approach is implemented in DIET where a user can define a task-graph-like structure using an XML file for the whole application [1]. The limitations of this approach are that the flow of execution is static and fixed and it is difficult and time consuming to write the XML description. Furthermore, DIET uses a specific function that executes the task graph from the XML file without creation of calls in the client code. This has the additional limitation that client computation is not allowed.

Workflow management systems, designed specifically for Grid computing, use data structures that are similar to the task graph. Many of these systems use specifically designed high level languages, such as the AGWL language for the Askalon system [7], YvetteML for YML [6] and Chimera for Pegasus [8]. While these high level languages are more expressive than simple XML files, they still lack some important functionalities limiting their use in Smart-GridRPC model. The AGWL language is a XBL-based-language with specific tags for generating basic control flow constructs. However, AGWL code needs to be pre-processed into a concrete XML file, which limits the possibility to dynamically change the execution flow at run-time. The YvetteML language has syntax similar to Pascal and C in order to describe complex workflows. However, it is missing an easy way to identify input and output data for remote computations. The Chimera language is a data driven language that allow for generation of complex workflows by checking the dependencies on existing files and selected output file name. However, the grammar and syntax of this language are not easy to understand and consequently its usage is not trivial.

In this paper, we have studied how the Algorithm Definition Language (ADL), in conjunction with SmartGridSolve, can be used to improve the execution of typical applications with irregular algorithms. We have conducted experiments demonstrating significant performance gains due to the use of ADL in applications that use conditional statements, iterative computations and adaptive methods. We have demonstrated that a programmer can improve the performance of their Grid application by using algorithm specification languages to describe the underlying algorithms. This work was supported by the Science Foundation Ireland.

References