A Quantitative Model for Predicting Cross-application Interference in Virtual Environments

Maicon Melo Alves\textsuperscript{a,}, Lúcia Maria de Assumpção Drummond\textsuperscript{a}
\textsuperscript{aInstituto de Computação, Universidade Federal Fluminense, Niterói, Brazil}

Abstract

Cross-application interference can affect drastically performance of HPC applications when running in clouds. This problem is caused by concurrent access performed by co-located applications to shared and non-sliceable resources such as cache and memory. In order to address this issue, some works adopted a qualitative approach that does not take into account the amount of access to shared resources. In addition, a few works, even considering the amount of access, evaluated just the SLLC access contention as the root of this problem. However, our experiments revealed that interference is intrinsically related to the amount of simultaneous access to shared resources, besides showing that another shared resources, apart from SLLC, can also influence the interference suffered by co-located applications. In this paper, we present a quantitative model for predicting cross-application interference in virtual environments. Our proposed model takes into account the amount of simultaneous access to SLLC, DRAM and virtual network, and the similarity of application’s access burden to predict the level of interference suffered by applications when co-located in a same physical machine. Experiments considering a real petroleum reservoir simulator and applications from HPCC benchmark showed that our model reached an average and maximum prediction errors around 4% and 12%, besides achieving an error less than 10% in approximately 96% of all tested cases.

Keywords: cross-application interference, virtual machine placement, cloud computing, high performance computing.

1. Introduction

Cloud computing is emerging as a promising alternative to execute HPC (High Performance Computing) applications. This new computational paradigm provides some attractive advantages when compared with a dedicated infrastructure, such as rapid provisioning of resources and significant reduction in operating costs related to energy, software licence and hardware obsolescence\textsuperscript{[17,12,4,13,27,53,6]}. However, some challenges must be overcome to bridge the gap between performance provided by a dedicated infrastructure and the one supplied by clouds. Overheads introduced by virtualization layer, hardware heterogeneity and low latency networks, for example, affect negatively the performance of HPC applications when executed in clouds\textsuperscript{[4,13,38,9,51]}. In addition, cloud providers usually adopt resource sharing policies that can worse even more HPC applications performances. Typically, one physical server can host many virtual machines holding distinct applications\textsuperscript{[48]}, that may contend for shared and non-sliceable resources like cache and main memory\textsuperscript{[17,19,20,26,17,46]}, reducing significantly their performances.

In order to address this problem, in\textsuperscript{[37]} a classification based on the Thirteen Dwarfs, which categorizes an application from its computational method, was used to decide which Dwarf classes could be co-located in a same physical machine without interference, i.e., keeping their original performances. Another work,\textsuperscript{[26]}, classifies HPC applications according to their cache access pattern. So, applications are classified within three SLLC access classes called: (i) cache-pollution, (ii) cache-sensitive and (iii) cache-friendly. From such classification, they claimed that a cache-pollution application, which presents weak-locality and large cache working set, should be primarily co-located with a cache-friendly application in order to alleviate cross-interference.

Those approaches, called here qualitative, because consider general characteristics of HPC applications, do not determine precisely the cross-application interference. Concerning the Dwarfs classification proposal, our experiments showed that the applications PTRANS and DGEMM\textsuperscript{1} belonging to the same Dwarf class, Dense Linear Algebra, presented distinct interference levels when they were co-located with themselves. Furthermore, our results also revealed that PTRANS presented distinct interference levels in face of instances of different sizes, allowing to assert that the interference level can vary with the amount of data computed by the application. Also, in\textsuperscript{[26]}, two cache-friendly applications, EP and IS\textsuperscript{2}, presented distinct interference levels when co-located with the same cache-pollution application, CG. Although both applications present a

\textsuperscript{1}PTRANS and DGEMM belong to the set of applications provided by the High Performance Computing Challenge (HPCC) benchmark

\textsuperscript{2}EP and IS belong to the set of applications provided by the Nas Parallel Benchmark (NPB)
compatibility cache access behavior, IS performed a higher number of memory references per second [20] what could explain why IS presented a higher interference level than EP.

Those results indicate that an approach that considers the amount of accesses to shared resources, could be a better strategy to determine more precisely the interference among applications co-located in a same physical machine. In this context, in [20] the relation between SLLC access burden and resulting cross-application interference was investigated. Although that work is a step forward when compared with the others, our experiments showed that other shared resources, besides SLLC, can also influence the interference level of co-located applications and should be considered as well. Moreover, all those related works only indicate whether applications should be or not co-located, but does not quantify the interference level between them.

In addition, our experimental tests revealed that the interference can also be influenced by the similarity of application’s access burden. When applications co-located in the same host present a high level of access burden similarity for a given shared resource, they evenly compete for this resource which, in turn, leverages the level of interference suffered by these applications. Thus, besides the amount of simultaneous access performed to shared resources, the similarity of application’s access burden should also be considered when investigating the cause of interference.

In this paper, we propose a quantitative model for predicting interference among applications co-located in a same physical machine by considering the amount of simultaneous accesses to shared resources and the similarity of application’s access burden. In order to predict that interference level, our proposed model considers the effect that SLLC, DRAM and virtual network concurrent accesses impose in cross-application interference. Those three resources are considered particularly critical because (i) SLLC and DRAM are shared among cores of a processor and, (ii) virtual network, although not a hardware resource, is emulated by the hypervisor which is a central component shared by all virtual machines [58] [3].

In order to build this prediction model, at first we proposed an application template from which synthetic applications with distinct access patterns to each shared resource are generated. We measured the interferences, when those applications were executed concurrently, and generated an interference dataset containing these results. Then, our quantitative model was built by applying the Multiple Regression Analysis (MRA), one of the most widely statistical procedures used for treating multivariate problems, over that interference dataset. Note that MRA is a powerful and well-known technique to build a model capable of predicting an unknown value of a response variable from the known values of multiple independent variables [51] [5] [22] [34] [40].

We validated the prediction model by using a real petroleum reservoir simulator, called Multiphase Filtration Transport Simulator (MUFITS) [11] [11], and applications from a well-known computing benchmark, the High Performance Computing Challenge (HPCC) [14] [31] [24]. Those applications were executed with different instances as input and results showed that our model predicted cross-application interference with a maximum and average errors of 12,03% and 4,06%, respectively. Besides that, the prediction error was less than 10% in 95,56% for all tested cases.

Thus, the main contributions of this work are the following:

• An interference prediction quantitative model that takes into account the amount of simultaneous access to SLLC, DRAM and virtual network, and the similarity of application’s access burden to predict the interference level suffered by co-located applications.

• An application template able to generate applications with distinct access rates to SLLC, DRAM and virtual network.

• A systematic evaluation of interference suffered by co-located applications before distinct levels of access to shared resources.

• An evaluation of model precision by considering a real reservoir petroleum simulator and applications from a well-known HPC benchmark.

At last, it is worth mentioning that the recent growth in the number of cores available in newer processors can increase even more the number of applications hosted in a same physical machine. In order to run HPC applications in those systems, Virtual Machine Placement (VMP) strategies will have to include efficient solutions for the cross-application interference problem.

The remainder of this paper is organized as follows. Section 2 presents works from the related literature. Section 3 presents the experiments executed to generate an interference dataset. Section 4 describes the model for predicting interference. The Model validation is discussed in Section 5. Finally, conclusions and future work are presented in Section 6.

2. Related Works

In this section, related works that investigated or just introduced the cross-application interference problem are presented. Some works presented the cross-application interference, but did not propose a solution to determine or alleviate this problem. Yokoyama [59] and Basto [8] accomplished interference experiments by using benchmark applications in order to generate a static matrix of interferences. Such matrix was further used as the basis for their proposed interference-aware VMP strategies. They evaluated their VMP strategies just using applications previously used in interference experiments. Thus, unlike our work, those papers did not present a solution to determine interference among co-located applications.

Other works, besides introducing interference, proposed a naive or limited approach to explain this problem. Jersak et al. •

In March of 2016, Intel® launched processor E5-2600 v4, codename Broadwell-EP, which is endowed with 22 cores. Thus, a physical server that supports two of these processors, such as Supermicro® 1028U-TN10RT+, provides 44 cores in total.
Rameshan et al. [47] proposed a mechanism to prevent latency sensitive applications from being adversely affected by best-effort batch applications when co-located in a same physical machine. In such proposal, latency sensitive applications report to mechanism whenever they are under interference. Then, the mechanism uses information collected in that instant to predict when latency application will suffer interference again. From this prediction, the mechanism throttles the batch application before it imposes interference to latency application one more time. Thus, that work just proposed a way to work around the interference suffered by a specific class of application by monitoring the conditions that lead to occurrence of the interference. So, the root of interference problem was not investigated and, as consequence, a solution to determine interference suffered by any set of applications was not proposed.

Other works, however, investigated the cross-application interference problem in a broader sense and proposed solutions to determine or alleviate interference experienced by co-located applications in general.

Mury et al. [37] argued that cross-application interference could be determined by adopting a classification of applications. Such qualitative approach is based on the Thirteen Dwarfs which classifies applications according to computational methods usually adopted in scientific computing. Such classification is not suitable to determine interference because our experiments showed that two applications belonging to Dense Linear Algebra class presented distinct interference levels. Besides that, our results also pointed out that a same application, namely PTRANS, can present distinct interference levels when solving instances with different sizes. Actually, experiments conducted in [20] also showed this same behavior when applications EP and LU presented distinct interference levels when solving also instances of different sizes.

Jin et al. [26] classified applications in three SLLC access classes called (i) cache-pollution, (ii) cache-sensitive and (iii) cache-friendly. These classes were further used to propose a VMP strategy with goal to alleviate interference by co-locating applications with compatible SLLC access profiles. That work claimed that cache-pollution applications should be preferably co-located with cache-friendly applications rather than being co-located with cache-sensitive ones. However, through some practical experiments they showed that approach may fail. More specifically, EP and IS, classified as cache-friendly, suffered distinct interference levels when co-located with CG, categorized as a cache-pollution application. Besides that, although both CG and FT were classified as cache-pollution applications, CG did not present interference when co-located with itself, while FT suffered an interference when co-located with CG. These results show that a qualitative approach based on SLLC access pattern is not suitable to determine cross-application interference precisely.

Unlike the aforementioned works, Gupta et al. [20] adopted a quantitative approach to investigate cross-application interference. They studied the relation between interference and the number of SLLC references per second performed simultaneously by co-located applications. As a result, they identified a maximum access limit that ensures a free interference co-location. Although this work proposed a quantitative strategy to explain interference problem, only one shared resource, SLLC, was considered. Our experiments showed that others shared and non-sliceable resources such as virtual network can also influence interference and, consequently, should be systematically evaluated.

Moreover, two of the previously described works, by Gupta et al. [20] and by Jin et al. [26], just inform whether applications should be or not co-located, without quantifying the level of interference suffered by them. However, the information about interference level can enrich the VMP process, specially in cases where only applications presenting high cross-interference levels are available.

To the best of our knowledge, this paper is the first one that proposes a quantitative model for predicting cross-application interference level by considering accesses to SLLC, DRAM and virtual network, jointly. We claim that a quantitative approach, that considers the amount of accesses of co-located applications to shared resources simultaneously, is more suitable to determine cross-application interferences.

3. Generating a Cross-application Interference Dataset

In order to create an interference dataset, several co-locating synthetic applications with distinct access levels were executed and evaluated.

Those synthetic applications with distinct access patterns to each shared resource were obtained from a template with different input parameters.

Next, some preliminary concepts are presented in subsection 3.1. Then, the proposed application template is described in subsection 3.2. In subsection 3.2.1, we present the used synthetic applications and in subsection 3.3 results of concurrent executions of these synthetic applications are presented.

3.1. Preliminary Concepts

We present here two fundamental definitions about cross-application interference used along this paper: the accumulated access to shared resources and the interference level suffered by co-located applications.

As defined in Equation 1, the access of an application $i$ to a shared resource $s$ is equal to the sum of access of all virtual machines holding this application to this shared resource, where $nV_i$ is the total number of virtual machines hosting $i$ and $V_{i,j,s}$ is...
the amount of access of virtual machine \( V_i \) to a shared resource \( s \). In this work the amount of access to LLC and DRAM are measured in terms of millions of references per second (MR/s), while the access to virtual network is expressed as the amount of megabytes transmitted per second (MB/s).

\[
A_{i,s} = \sum_{j=1}^{n_v} V_{i,j,s}
\]

From Equation 1, we defined the accumulated access of all applications to a shared resource. Thus, as defined in Equation 2, this accumulated access to a shared resource \( s \) is equal to the sum of access of all applications co-located in same physical machine, where \( n_A \) is the total number of applications co-located in same physical machine and \( A_{i,s} \) is the amount of access of application \( A_i \) to shared resource \( s \). This accumulated access represents the total amount of pressure to a shared resource in a given time interval.

\[
T_s = \sum_{i=1}^{n_A} A_{i,s}
\]

We argue that the amount of accumulated access to specific shared resources is directly related to the slowdown suffered by co-located applications. In this work, slowdown is defined as the ratio of the execution time achieved by application when executed concurrently with co-located applications \( C_{i,X} \) to the one achieved from isolated execution \( T_i \) less 1, where \( X \) is the set of applications co-located in a same physical machine, as shown in Equation 3.

\[
S_{i,X} = \frac{C_{i,X}}{T_i} - 1
\]

Then, the cross-application interference level is defined as the average slowdown of applications when co-located with other ones in a same physical machine.

For example, suppose that the execution times of two applications, namely A and B, in a dedicated processor were equal to 60 and 80 seconds. Suppose also that these both applications, when concurrently executed in that processor, spent 100 seconds. In such scenario, the slowdown of applications A and B would be, respectively, 67\% and 25\%, which represents how much additional time these applications needed to complete their executions when co-located in a same processor. The cross-application interference level between applications A and B would be 46\%. Thus, applications A and B, would suffer, in average, 46\% of mutual interference when co-located in a same processor.

### 3.2. Generating Synthetic Applications

The access contention to shared resources is the main cause of the interference suffered by applications co-located in a same physical machine. To study cross-application interference, most of related work\[2\] employs real applications provided by traditional HPC benchmarks. However, a real application does not allow to control the number of accesses to each shared resource, and consequently, to evaluate systematically the relation between concurrent accesses and the resulting interference. Thus, we propose an application template from which synthetic applications with distinct access levels are created. From this template, we can create an application which performs a high access pressure to LLC, while keeping a low access level to virtual network, for example. Thus, a set of synthetic applications created from that template allows to observe interference before different levels of accesses to LLC, DRAM and virtual network.

In order to represent the usual behavior of HPC applications\[49\], the proposed synthetic application template presents, alternately, two distinct and well-defined phases. The first one, called Computation Phase, represents the phase at which the application performs tasks involving calculation and data movement. The other one, namely Communication Phase, is the phase where the application exchanges information among computing pairs.

The proposed synthetic application template is shown in Algorithm 1. Firstly, the synthetic application executes the Main Loop (lines 1 to 13) whose total number of iterations is controlled by parameter \( \omega \). This parameter leverages the total execution time of application. Next, the synthetic application executes Computation Phase Loop (lines 2 to 9) at which it performs the Computation Phase with the number of iterations defined by \( \alpha \). This Computation Phase is based on the benchmark STREAM which is widely used to measure performance of memory subsystems\[41\] [57]. In order to measure sustainable memory bandwidth, this benchmark executes four simple vector kernels, as presented in Table 3.2. Because SUM presents the highest tax of memory access, it was chosen to be included in the proposed template.

---

**Algorithm 1 Synthetic application template**

```
1: /* Main Loop*/
2: for \( x=1 \) to \( \omega \) do
3:     /* Computation Phase Loop*/
4:     for \( y=1 \) to \( \alpha \) do
5:         /* Memory Access Loop*/
6:         for \( i=1 \) to \( \gamma \) step \( \delta \) do
7:             /* Compute-intensive Loop*/
8:             A[i] = B[i]+C[i];
9:         end for
10:     end for
11: end for
12: end for
13: /* Communication Phase Loop*/
14: for \( z=1 \) to \( \beta \) do
15:     All-to-All-Communication(D,A);
16: end for
```

The SUM operation is executed by the inner loop Memory Access Loop (lines 3 to 8) which is controlled by two input parameters, \( \gamma \) and \( \delta \). The first one defines the sizes of vectors...
A, B and C, and is indirectly used to determine application’s Working Set Size (WSS) \([28, 29]\). A small WSS usually increases application’s cache hit ratio because all data needed by it in a given time interval can be entirely loaded in cache. On the other hand, when the application has a WSS greater than cache capacity, its cache hit ratio decreases because all data is fetched from main memory. Thus, WSS can be used to control cache hit ratio and, consequently, control the number of DRAM references per second also.

| Name  | Operation            | Bytes per Iteration |
|-------|----------------------|---------------------|
| COPY  | \(a[i] = b[i]\)      | 16                  |
| SCALE | \(a[i] = b[i]*q\)    | 16                  |
| SUM   | \(a[i] = b[i] + c[i]\) | 24                 |
| TRIAD | \(a[i] = b[i] + c[i]*q\) | 24            |

Table 1: STREAM kernels

The second parameter of Memory Access Loop, namely \(\delta\), controls the step at which the vector elements are accessed. Thus, when \(\delta\) is equal to 1, all elements of vectors A, B and C are accessed consecutively, resulting in a high cache hit ratio. Otherwise, when \(\delta\) is set to a high value, more data are fetched from main memory, resulting in performance degradation. In other words, this parameter provides another way to control cache hit ratio and to manipulate the number of DRAM references per second.

Thus, the number of DRAM references per second and application’s cache hit ratio can be controlled by performing a fine tuning of both parameters \(\gamma\) and \(\delta\). When the application presents a high cache hit ratio, DRAM receives few references per second because data is already available in SLLC. Likewise, the number of memory references increases when application performs a low cache hit ratio.

Besides controlling DRAM access, these both parameters allow to handle the number of SLLC references per second as well. When the application presents a low cache hit ratio, the number of SLLC references per second decreases. This happens because, before accessing new data, the previous referenced data, not found in SLLC, has to be fetched from DRAM. Consequently, the rate at which application performs data accesses is reduced, decreasing also the number of SLLC references per second. On the other hand, when the application presents a high cache hit ratio, the number of SLLC references per second increases. Because most data is rapidly fetched from SLLC, more memory accesses can be performed per second.

After performing the SUM operation (line 4), synthetic application executes Compute-intensive Loop which repeatedly calculates the square root of variable \(T\) (line 6). This loop, whose number of iterations is defined by \(\beta\), allows to make application more or less compute-intensive. Note that when \(\beta\) is set to a high value, the number of memory references decreases. This happens because variable \(T\), being frequently referenced, is kept stored in the first cache level (cache L1), preventing memory subsystem lower levels of being accessed. As a result, both number of SLLC and DRAM references per second decreases. Thus, together with \(\gamma\) and \(\delta\), \(\beta\) is also used to manipulate the number of DRAM and SLLC references per second.

After Computing Phase Loop execution, synthetic application performs Communication Phase by executing Communication Phase Loop (lines 10 to 12) whose number of iterations is determined by input parameter \(\beta\). This phase is based on MP BENCH benchmark \([16]\). From all MPI operations executed by this benchmark, MPI Alltoall was particularly interesting for our work because it is widely used in scientific applications. When using this collective operation, all application’s processes send and receive to/from each other the same amount of data \([50, 23, 29]\).

For each Communication Phase Loop iteration, the application executes All-to-All-Communication() function (line 11) that employs MPI Alltoall of a vector \(D\) whose size is defined by the input parameter \(\lambda\). So, this input parameter is used to handle the number of bytes transmitted in the virtual network.

Synthetic applications with distinct access profiles can be generated by varying properly all of these aforementioned input parameters, whose descriptions are summarized as next.

- \(\omega\): application’s total number of iterations.
- \(\alpha\): total number of iterations of Computation Phase.
- \(\beta\): total number of iterations of Communication Phase.
- \(\gamma\): Working Set Size (WSS).
- \(\delta\): step at which the vector elements in Memory Access Loop are accessed.
- \(\theta\): level of compute-intensiveness.
- \(\lambda\): amount of data exchanged among processes.

Unlike adopting real applications, with this proposed synthetic application template, several applications that perform distinct access pressure to SLLC, DRAM and virtual network can be generated, providing a proper way to investigate systematically the relation between number of accesses and cross-application interference.

### 3.2.1. Used Synthetic Applications

In this subsection, we present the set of synthetic applications generated from the previously presented application template. Applications with distinct access rates were generated, considering three target access levels for each of the three shared resources. The access rates to each shared resource are expressed by distinct metrics, such as number of references to memory per second or transmitted bytes per second, and the range of those values are also different. To treat those access rates jointly, we normalized those values in an interval between 0.0 and 1.0, where score 1.0 represents the highest possible access rates achieved by an application based on the proposed template, and score 0.0 represents no access. These scores, in our work, represent different access levels to the shared resources. Then, we created applications with high, medium and low access levels to SLLC, DRAM and virtual network, where the high access level corresponds, in our proposal, to the highest access rate to each
shared resource, and medium and low access levels correspond to 50% and 10% of this high access rate, respectively.

To generate those applications with these distinct access levels, we varied input parameters of application template and monitored resulted access rate to each shared resource by using monitoring tools such as PAPI (Performance Application Programming Interface) [10], OProfile [52] and SAR (System Activity Report) [44].

We executed this set of synthetic applications in an Itautec MX214 server whose configuration details are described in Table 3.2.1. As illustrated in Figure 1, this server is equipped with two NUMA nodes interconnected by a QPI (Quick Path Interconnect) of 6.4 GT/s, where each NUMA node has 24GB of DRAM memory and is endowed with a Intel Xeon X5675 3.07GHz processor. Each processor has six cores that share a 12MB SLLC unit. Moreover, the virtual environment was provided by KVM hypervisor running on top of Ubuntu Server.

| Model         | Itautec MX214          |
|---------------|------------------------|
| CPU           | 2x Intel Xeon X5675 3.07 GHz |
| DRAM          | 48 GB DDR3 1333 MHz    |
| Disk          | 5.8 TB SATA 3 GB/s     |
| QPI           | 6.4 GT/s               |
| S.O.          | Ubuntu 15.04           |
| Kernel        | 3.19.0-15              |
| Hypervisor    | KVM                    |
| Hardware Emulation | Qemu 2.2.0           |

Table 2: Configuration of server used in experiments

In our proposal, each application uses six virtual machines, each one deployed in one core, allocating 4GB of main memory. We used CPU affinity to deploy half of the virtual machines of the application in each NUMA node, i.e., three virtual machines were deployed in “NUMA Node #1”, while the others were deployed in “NUMA Node #2”, in a dedicated machine. In this scenario, the access of synthetic application to shared resources, specifically SLLC and DRAM, is balanced over two NUMA nodes, avoiding self-interference. Moreover, that configuration will be helpful to evaluate cross-application interference as discussed in the next section.

The set of the generated synthetic applications and the corresponding execution profiles are described in Table 3.2.1. All applications execute the same number of iterations (\( \omega = 25 \)) and parameters \( \alpha \) and \( \omega \) were set to ensure that they spent approximately the same amount of time executing Computation and Communication Phases. Moreover, all scores were rounded to one decimal place. This explains, for example, why applications S1 and S7, although have presented distinct absolute values, were classified in the same SLLC score.

Applications S1, S7 and S13 achieved the highest SLLC number of references per second. In order to reach this high SLLC access, we adjusted the input parameters to ensure that all memory references were directly satisfied by SLLC, what resulted in a 0.0 DRAM score. Thus, although score 0.0 was not considered as one of the three target access levels, there is no way to achieve the highest number of SLLC references per second without reducing drastically the number of accesses to DRAM.

On the other hand, the number of memory references satisfied by SLLC has to decrease to rise the number of DRAM references per second. To achieve a high DRAM access, all memory references should result in accesses to main memory, i.e., the SLLC hit ratio must be close to 0%. However, even in that case, the number of SLLC references per second is not equal to zero, because all references to DRAM are also treated by SLLC. This explains why applications S4, S10 and S16, which achieved the highest number of DRAM references per second, exhibited a SLLC score equal to 0.3.

Thus, concerning the memory subsystem, we were not able not generate all possible combinations involving the three access levels. A high number of accesses to SLLC implicates in a low number of accesses to DRAM. As a consequence, it is not possible to generate an application which both SLLC and DRAM scores equal to 1.0 or an application which performs, simultaneously, a high and medium access level to SLLC and DRAM, for example.

Besides that, that behavior also resulted in some unexpected combinations as the one presented by application S4, that presented DRAM and SLLC scores equal to 1.0 and 0.3, respectively, though this last score was not considered as one of the target access levels.

At last, concerning virtual network, the highest amount of transmitted bytes was achieved by increasing input parameter \( \lambda \) up to reaching the maximum amount of data that the hypervisor is able to handle at same time. We varied \( \lambda \) to find out the virtual network saturation threshold. When this limit is exceeded, the amount of bytes transmitted per second decreases, regardless of
the increasing of $\lambda$.

Although we did not generate all possible combinations of applications, we were able to create a synthetic workload with distinct computational burden, suitable for conducting a deep evaluation of the cross-application interference problem.

### 3.3. Measuring Cross-applications Interference

In this section, we present experiments to determine cross-applications interference. The previously presented synthetic applications were executed in a two-by-two fashion to obtain the resulting interference level in several cases. Because each synthetic application used half of available resources (memory and CPU), we were able to co-locate two of those applications in the physical machine, without exceeding the available resources in the system. That full allocation represents a realistic scenario, usually found in clouds environments, where all resources available in a physical machine are fully allocated to maximize resource utilization [43] [48].

![Histogram of Resulted Interference Levels](image)

**Figure 2:** Histogram of resulted interference levels achieved from synthetic experiments

The generated synthetic applications do not present exactly the same execution time, so to keep concurrency among co-located applications until the end of the experiment, the smaller execution time application was re-started automatically as many times as necessary to cover the entire execution of the longer application. We adopted such approach to fairly measure the interference suffered by both applications, regardless their execution times.

As the synthetic workload is composed of 18 applications, our interference experiments comprised 171 concurrent executions whose results are summarized in Figure 2. Those results show that cross-applications interference can vary drastically, from 10% to 189%, depending on which applications are co-located in the same physical machine. As can be seen in Figure 2, around 54% of the total co-executions (93 occurrences) achieved an interference level less than 50%, while 37% of co-locations (63 occurrences) suffered interference levels between 50% and 100%. Besides that, in around 9% of all cases (15 occurrences) co-location applications reached interference levels greater than 100%. These results presented a coefficient of variation close to 56% which allows to assert that these synthetic experiments comprised a large range of interference levels.

![Scatter plot of SLLC accumulated score against interference level](image)

**Figure 3:** Scatter plot of SLLC accumulated score against interference level

An initial analysis accomplished in these results revealed that there is a correlation between interference level and SLLC accumulated score. As can be seen in Figure 3, interference level tends to increase as SLLC accumulated score rises. Indeed, the Pearson’s correlation coefficient between SLLC accumulated score and interference level is around 0.76, indicating a strong, positive and linear relationship between these both variables. Thus, this observation corroborates the hypothesis that the amount of access performed in shared resources can really influence the interference suffered by co-located applications.

In addition, these experiments allowed to confirm that mutual access performed in other shared resources besides SLLC can also impact the interference level. Consider, for example, SLLC accumulated score equal to 0.40, in Figure 3 it may occur in cases with distinct interference levels. In other words, although SLLC access presents a strong correlation with interference level, there is another factor influencing it.

Actually, the interference level increases as virtual network access also does. As illustrated in Figure 4 when virtual network accumulated score is equal to 0.2 and 2.0, the corresponding interference levels are around 28% and 60%, respectively. For the same SLLC accumulated score, the interference level suffered by co-located applications varies more than 30% depending on the amount of access to virtual network.

Moreover, some co-locations, even though performed almost the same amount of accumulated access to all shared resources, present interference levels that varied in more than 45%. In the subset of interference results, listed in Table 3.3, for example, 4

![Histogram of Resulted Interference Levels](image)

**Table 3.3:** Histogram of resulted interference levels achieved from synthetic experiments

Also known as relative standard deviation, the coefficient of variation is defined as the ratio of the standard deviation to the mean.
the co-location “S15xS7” suffered an interference level 46% higher than the co-location “S14xS8”, although both have the same virtual network accumulated score, 1.5, and differ slightly about DRAM and SLLC accumulated scores. Applications S15 and S7 present, individually, distinct SLLC access values, the former performs much less access to SLLC than the latter. This explains why this co-location does not present a high interference level, even achieving a high SLLC accumulated access. On the other hand, S15 and S7, although present a similar SLLC accumulated access, evenly compete for SLLC, resulting in a high interference level. As can be seen in Table 3.3, this also happens in co-locations that present virtual network accumulated scores equal to 0.6 and 0.2.

![Figure 4: Scatter plot of virtual network accumulated score against interference level when SLLC was equal to 0.40](image)

From results reached on these experiments, we can draw some preliminary conclusions about cross-application interference.

- There is a strong correlation between amount of simultaneous accesses to SLLC and level of interference suffered by applications.
- Although SLLC access rate presents a strong correlation with interference level, the simultaneous access to other shared resources, such as virtual network, can contribute to increase interference as well.
- Besides total amount of access to shared resources, the similarity between application’s access burden can also impact interference level suffered by co-located applications.

That scenario justifies the adoption of a quantitative approach for predicting the interference level suffered by co-located applications. As shown, the cross-application interference level is influenced by the collective effect of more than one variable, what...pareaqui treated as a multivariate problem.

| Co-execution | Accumulated Score | Interference Level |
|---------------|-------------------|--------------------|
|               | SLLC | DRAM | NET  |
| S1 x S3       | 1.1  | 0.1  | 0.2  | 34.10% |
| S2 x S2       | 1.0  | 0.2  | 0.2  | 71.12% |
| S13 x S3      | 1.1  | 0.1  | 0.6  | 31.51% |
| S14 x S2      | 1.0  | 0.2  | 0.6  | 71.83% |
| S15 x S7      | 1.0  | 0.2  | 1.5  | 41.67% |
| S14 x S8      | 1.1  | 0.1  | 1.5  | 87.97% |

Table 4: Subset of synthetic interference experiments

So, besides accumulated access performed to shared resources, the similarity of application’s access burden has a direct impact in interference level suffered by applications when co-located in a same machine. Indeed, this justifies the difference between interference levels achieved by co-locations listed in Table 3.3.

In order to measure the level of similarity between two applications, we define in Equation 4 the similarity factor. The similarity factor of two applications regarding to a shared resource $s$ is calculated as the difference between 1 and the absolute value resultant from the difference between the amount of individual access that applications $i$ and $j$ perform in a shared resource $s$. From Equation 4 we defined the global similarity factor as being the average of all similarity factors calculated for each pair of applications co-located in a physical host.

$$F_{i,j,s} = 1 - |A_{i,s} - A_{j,s}|$$ (4)

From results reached on these experiments, we can draw some preliminary conclusions about cross-application interference.

- There is a strong correlation between amount of simultaneous accesses to SLLC and level of interference suffered by applications.
- Although SLLC access rate presents a strong correlation with interference level, the simultaneous access to other shared resources, such as virtual network, can contribute to increase interference as well.
- Besides total amount of access to shared resources, the similarity between application’s access burden can also impact interference level suffered by co-located applications.

That scenario justifies the adoption of a quantitative approach for predicting the interference level suffered by co-located applications. As shown, the cross-application interference level is influenced by the collective effect of more than one variable, what...pareaqui treated as a multivariate problem.

4. Quantitative Cross-application Interference Prediction Model

In this section, we describe process accomplished for building our proposed quantitative prediction model by using Multiple Regression Analysis. First, in subsection 4.1 we briefly introduce Multiple Regression Analysis, while in subsection 4.2 we describe how this technique was employed to build our prediction model.

4.1. A Brief Introduction to Multiple Regression Analysis

Multiple Regression Analysis (MRA) is a multivariate statistical technique that allows to explain the relationship between one dependent variable and, at least, two independent variables. This technique is used to create a model, a.k.a. statistic variable, able to predict the value of the dependent variable from the known values of independent variables [40].

Basically, MRA is comprised of four macro steps as illustrated in flowchart of Figure 5. Firstly, in Variables Selection step, researcher selects the most likely variables to explain the behavior of the response variable. Although some statistical techniques such as matrix of correlation can provide some insights about what variables must be chosen, this process is mainly guided by the researcher’s knowledge about the problem [22] [40].

After that, researcher executes the Model Estimation step, where the terms of the model are determined and their coefficients are automatically estimated by using the Least Squares...
Method. Next, researcher proceeds to the Model Evaluation step in order to evaluate goodness-of-fit level, i.e., how satisfactorily the estimated model fits to data used in building process. Besides that, researcher also assesses statistical significance of regression and coefficients. In case that estimated model does not present a satisfactory goodness-of-fit level or a desired statistical significance level, a new model should be estimated by executing, again, the Model Estimation step. Otherwise, estimated model is ready to be validated in Model Validation step by using an “unseen” dataset, i.e, a dataset not used previously during the process of model estimation [22][40][34][54].

Our quantitative model for predicting interference is described in Equation 5 whose terms are listed in Equations 6 and 8. As can be seen in estimated model, global similarity factors, namely $G_{sllc}$, $G_{dram}$ and $G_{net}$, were employed to weigh the influence that accumulated accesses, namely $T_{sllc}$, $T_{dram}$ and $T_{net}$, impose in interference. Moreover, the total amount of access performed in DRAM was pondered by SLLC accumulated access since all access requests to DRAM are firstly treated in SLLC. At last, it is worth mentioning that the constant as well as quadratic terms were not included in model in order to make it as simple as possible.

\[
I = 0.7498 * T1 + 0.1598 * T2 + 0.1456 * T3
\]  
(5)

Where,

\[
T1 = T_{sllc} * G_{sllc}
\]  
(6)

\[
T2 = T_{net} * G_{net}
\]  
(7)

\[
T3 = T_{dram} * T_{sllc} * G_{sllc}
\]  
(8)

From coefficients estimated by each term, we can state that the simultaneous and accumulated access to SLLC really imposes the higher influence in interference. However, as previously discussed, the access to other shared resources can also affect interference since terms regarding to virtual network and DRAM, respectively T2 and T3, presented, together, a coefficient very close to 0.31. Thus, depending on the value of SLLC accumulated score, the interference will be primarily determined by the access performed to DRAM and virtual network.

This model presented an Adjusted Coefficient of Regression, a.k.a. Adjusted R-squared ($R^2_{adj}$), around 0.912 which means that 91.2% of variance present in dataset can be explained through this estimated model. In other words, this high $R^2_{adj}$ indicates that the model is well fitted to dataset used in building process which, in turn, allows it to perform more accurate predictions about the dependent variable.

In addition, we assessed statistical significance of the regression model and coefficients of each term by applying hypothesis test F. At a level of significance ($\alpha$) of 0.05, test F revealed that regression as well as its coefficients can be considered as being statistically significant since resulted $p$-values were smaller than 0.00. These results indicate that the probability of each coefficient has been estimated just for this sample is practically 0%. In other words, this model has almost 100% chance to be able to predict interference level for any sample besides that one used to build model.

Although non specialized programs such as Excel and Matlab can be used for building a model from MRA, this process is usually accomplished by using commercial statistical packages such as Evies [35], SAS [2], and Minitab [53], or free software ones like Gretl [7] or R [45]. Such specific tools provides a full multivariate analysis toolbox that allows to perform a deep analysis on estimated model [56][39][36].

4.2. Model Building

By using Minitab version 17.1.0, we followed the aforementioned process to build our proposed model. At first, we executed the Variables Selection step in order to identify what variables should be selected as independent ones. As synthetic dataset was generated specifically to investigate interference, this selection process was straightforward. Therefore, we determined accumulated scores and global similarity factors to all of the three shared resources as independent variables and cross-application interference level as the dependent one. So, we expect to generate a model able to predict the interference level from the known values of accumulated scores and global similarity factors.

After Variable Selection step, we repeatedly executed both Model Estimation and Model Evaluation steps till reach a parsimonious model with satisfactory levels of goodness-of-fit and statistical significance. A parsimonious model is able to perform better out-of-sample predictions because, due to its simplicity, it is not usually overfitted to the sample [54].

Figure 5: Model building flowchart

**Variables Selection**

**Model Estimation**

**Model Evaluation**

*Yes*

Satisfactory levels of goodness-of-fit and statistical significance?

*No*

**Model Validation**
Moreover, an analysis accomplished on residuals showed that estimated model did not violate any of the MRA basic assumptions. Thus, residuals presented (i) linearity, (ii) homocedasticity and (iii) normal distribution.

5. Experimental Tests and Results

In this section, we describe experimental tests accomplished to assess the precision achieved by our model when predicting interference among co-located applications. In subsection 5.1, we describe the workload used for conducting such experimental tests. In subsection 5.2, we present predictions made by using our model, while in subsection 5.3, we evaluate how precisely these predictions match to interference levels achieved in real experiments.

5.1. Evaluation Workload

In order to evaluate the precision of our prediction model, we accomplished interference experiments by using an evaluation workload comprised of a real petroleum reservoir simulator, called MUFITS, and applications from High Performance Computing Challenge Benchmark (HPCC).

MUFITS is employed by petroleum engineers to study the behavior of petroleum reservoir across the time. From simulation results, they can make inferences about future conditions of the reservoir in order to maximize oil and gas production in a new or developed field. Basically, the simulator employs partial differential equations to describe the multiphase fluid flow (oil, water and gas) inside a porous reservoir rock. Reservoir simulation is one of the most expensive computational problems faced by petroleum industry since a single simulation can take several days, even weeks, to finish. Computational complexity of this problem arises from the high spatial heterogeneity of multi-scale porous media.

Besides MUFITS, we tested applications from HPCC, a widely adopted benchmark to evaluate performance of HPC systems. This benchmark provides seven kernels in total, but, only four of them, represent real HPC applications or operations commonly employed in scientific computing. A brief description of these four applications is as follows.

- **HPL**: solves a dense linear system of equations by applying the LU factorization method with partial row pivoting. This application, that is usually employed to measure sustained floating point rate execution of HPC systems, is the basis of evaluation for the Top 500 list.
- **DGEMM**: performs a double precision real matrix-matrix multiplication by using a standard multiply method. Even not being a complex real application, this kernel represents one of the most common operation performed in scientific computing, the matrix-matrix multiplication.
- **PTRANS**: performs a parallel matrix transpose. As their pairs of processors communicate with each other simultaneously, this application is a useful test to evaluate the total communications capacity of the network.
- **FFT**: computes a Discrete Fourier Transform (DFT) of very large one-dimensional complex data vector and is often used to measure floating point rate execution of HPC systems.

We considered, for each of those applications, distinct instances in order to certify that our proposal is able to precisely predict interference, regardless of the size of instance treated by applications. For MUFITS, we considered instances usually adopted in literature. The first one, labeled here as “I1”, concerns to a simulation of CO2 injection in the Johansen formation by using a real-scale geological model of the formation. The other one, labeled here as “I2”, is related to the 10th SPE (Society of Petroleum Engineers) Comparative Study. Both instances are available on MUFITS website.

For HPCC, we considered instances whose details are described in Table 5.1. We created these instances by adjusting parameters “#N”, “N” and “NB” which correspond, respectively, to the number of problems, the size of the problem treated by application and the size of the block. Remark that each input parameter has a specific meaning for each application. For example, in case of DGEMM, input parameter “N” is used to set the dimension of matrices to be multiplied, while this same parameter, in case of FFT, determines the size of vector of real numbers to be transformed to the frequency domain.

More detailed information about these input parameters can be found in HPCC website.

| Application | Instance | HPCC Parameters | #N | N | NB |
|-------------|----------|-----------------|-----|---|----|
| HPL         | I1       |                 | 1   | 18000 | 80 |
| DGEMM       | I1       |                 | 1   | 15000 | 80 |
| DGEMM       | I2       |                 | 1   | 3000  | 80 |
| DGEMM       | I2       |                 | 1   | 18000 | 80 |
| PTRANS      | I1       |                 | 1   | 24000 | 80 |
| FFT         | I1       |                 | 1   | 65000 | 10 |
| FFT         | I2       |                 | 1   | 40000 | 10 |

Table 5: HPCC applications instances description

5.2. Predicting Interference with Delfos

In order to assess model precision before distinct scenarios, we considered two co-locations schemes that resulted in 90 co-locations in total. In the first one, namely A, applications were co-located in a two-by-two fashion, where each application was executed by using instances I1 and I2. In this scenario, each one of those applications used 6 virtual machines except for FFT that used 4 virtual machines since this application restricts the number of process to a power of two. In the second co-location scheme, namely B, those applications were co-located in a three-by-three fashion, where each application used 4 virtual machines. Unlike A, in scenario B each application solved...
just instance I1. Moreover, each virtual machine used in both schemes has the same configuration as the one described in subsection 3.2.1 and, as performed in synthetic experiments, half of virtual machines allocated to each application was pinned to each NUMA node.

For predicting interference suffered by applications when co-located on schemes A and B, we executed individually each of one of those applications in order to obtain their access rates to each shared resource. As described in Table 5.2, FFT achieved the highest access rate to virtual network, while PTRANS, when solving I1, imposed the highest pressure to LLC and DRAM. Moreover, as DGEMM is an embarrassingly parallel application, it performed a very low access to virtual network. Remark, at last, that some applications decreased their access rates to shared resources when executing with four processors instead of six. This is expected since a same application, when executed with a lower number of processes, perform, usually, a lower amount of accumulated access to shared resources.

Considering individual profile of each application, we applied our quantitative model to predict what would be the interference suffered by those applications when co-located in accordance with schemes A and B. Prediction results point out that the minimum and maximum predicted interference levels would be equal to 1.53% and 43.10%, respectively. As expected, the lowest and highest interference levels were predicted for co-locations that involved, respectively, applications with low and high access rates to LLC, DRAM and virtual network. In other words, our model indicated that DGEMM and HPL would suffer a low cross-interference, while FFT and PTRANS would present the highest interference levels.

However, specifically to PTRANS, our model point out that interference suffered by this application would vary significantly depending on instance being solved. Our model indicated that PTRANS.I1.P6 would experience an interference level around 40% when co-located with itself in a two-by-two fashion, while PTRANS.I2.P6, when co-located in same conditions, would present an interference level of approximately 12%.

Moreover, our model predicted that PTRANS and DGEMM, although belonging to the same Dwarf class, namely Dense Linear Algebra, would present distinct interference levels when co-located with themselves. So, prediction results indicated that interference level resulted from co-location “PTRANS.I1.P6xPTRANS.I1.P6” would be approximately equal to 40%, while “DGEMM.I1.P6xDGEMM.I1.P6” would suffer an interference level close to 3%.

Furthermore, our quantitative model predicted that FFT.I1.P4 and MUFITS.I1.P4, although have presented similar LLC access rates, would suffer distinct interference levels when co-located with themselves in a three-by-three fashion. Specifically, our solution predicted that FFT.I1.P4 would present a mutual interference around 40%, while MUFITS.I1.P4 would suffer a cross-interference approximately equal to 12%.

5.3. Evaluating Precision of Interference Prediction

In order to evaluate the precision of our quantitative model, we executed all of the co-locations defined in schemes A and B and, for each co-location, we calculated the prediction error achieved by our solution. The prediction error is defined as the absolute value of the difference between interference level predicted by our model and the real interference level suffered by applications.

As can be seen in Figure 6, our model presented an average and maximum prediction errors equal to 4.06% and 12.03%, respectively. Moreover, in approximately 96% of all tested cases, our quantitative model presented a prediction error less than 10%. Such results revealed that our model, although have been built from a two-by-two fashion experiment, precisely predicted cross-interference for cases which three applications were executed simultaneously, as well.

Some interesting results are highlighted in Table 5.3. At first, as predicted by our model, experimental results showed that PTRANS really presented distinct interference levels when treating I1 and I2. Our quantitative model was able to predict interference of PTRANS regardless of the size of instance because it takes into account the amount of access that applications perform to shared resources. Indeed, as can be seen in Table 5.3 the amount of access that PTRANS performs to all shared resources when solving I1 is significantly higher than the one achieved when treating I2.

Besides that, those experimental results confirmed that PTRANS and DGEMM, even belonging to the same Dwarf class, presented distinct interference levels. This result allows to state that a qualitative approach based on Dwarfs classes is not enough to precisely determine interference. On the other hand, our model was able to predict that PTRANS and DGEMM would present, respectively, a high and a low interference levels.

At last, results also showed that LLC access contention is not the only cause for the cross-interference problem. FFT.I1.P4 and MUFITS.I1.P4, although have similar LLC access burden, suffered distinct interference levels. As depicted in Table 5.3 our model predicted satisfactorily interference suf-
ffered by these applications because it evaluates not only SLLC, but DRAM and virtual network access as well. Indeed, although both applications present similar SLLC access rates, FFT11.P4, which suffered a higher interference, performs a higher access to virtual network than MUFITS11.P4.

Therefore, all these findings allow to assert that a solution based on Dwarf’s classes or that evaluates just SLLC access contention is not suitable to determine interference suffered co-located applications. Our proposed model satisfactorily predicted interference for these specific cases because it takes into account the amount of simultaneous access to SLLC, DRAM and virtual network, besides considering access burden similarities among co-located applications.

6. Conclusions and Future Work

In this paper, we presented a quantitative model that takes into account the amount of simultaneous access to SLLC, DRAM and virtual network, and the similarity of application’s access burden to predict the level of interference suffered by applications when sharing a same physical machine. Experimental results, considering a real petroleum reservoir simulator and applications from HPCC benchmark, showed that our solution was able to predict interference with an average and maximum errors around 4% and 12%, respectively. Besides that, in 96% of all tested cases, our solution reached a prediction error less than 10%.

More specifically, our experimental tests showed that our solution could correctly predict interference of co-located applications even for cases which interference suffered by the same application varied before distinct instances. In addition, our model was able to precisely predict interference regardless the number of applications being co-executed in same host, though it was built by using a dataset generated from a two-by-two fashion experiment. Furthermore, our model could predict interference for co-locations that, even presenting similar SLLC access burden, achieved distinct interference levels. Our model accurately predicted interference in this case because it considers, besides SLLC, other shared resources such as DRAM and virtual network.

In future works, we expect to evaluate the influence that concurrent access performed to other shared resources, like disk, impose in cross-application interference. Moreover, we are also interested in investigating whether the total amount of allocated memory has a direct impact in interference suffered by co-located applications, besides assessing other metrics of virtual network such as the number of packets transmitted, for example. Furthermore, it would be interesting to evaluate whether interference varies before distinct hardware configuration in order to incorporate this issue to our prediction model.

References

[1] Afanasyev, A., Kempka, T., Kühn, M., Melnik, O., 2016. Validation of the mufs reservoir simulator against standard industrial simulation tools for o2 storage at the ketrin pilot site. In: EGU General Assembly Conference Abstracts. Vol. 18. p. 6883.

[2] Agresti, A., Kateri, M., 2011. Categorical data analysis. Springer.

[3] Albericio, J., Ibáñez, P., Vital, V., Llaberia, J. M., 2013. The reuse cache: downsizing the shared last-level cache. In: Proceedings of the 46th Annual IEEE/ACM International Symposium on Microarchitecture. ACM, pp. 310–321.

[4] Alves, M., Drummond, L., 2014. Análise de desempenho de um simulador de reservatórios de petróleo em um ambiente de computação em nuvem. In: XV Simpósio em Sistemas Computacionais de Alto Desempenho (WSCAD 2014).

[5] Atici, U., 2011. Prediction of the strength of mineral admixture concrete using multivariable regression analysis and an artificial neural network. Expert Systems with Applications 38 (8), 9609–9618.

[6] Atif, M., Kobayashi, R., Menadue, B. J., Lin, C. Y., Sanderson, M., Williams, A., 2016. Breaking hpc barriers with the 56ge cloud. Procedia Computer Science 93, 3–11.

[7] Baoocchi, G., Distaso, W., 2003. Grett: Econometric software for the gnu generation. Journal of Applied Econometrics 18 (1), 105–110.

[8] Basto, D. T., 2015. Interference aware scheduling for cloud computing, Master’s thesis, Universidade do Porto.

[9] Chen, L., Patel, S., Shen, H., Zhou, Z., 2015. Profiling and understanding virtualization overhead in cloud. In: Parallel Processing (ICPP), 2015 44th International Conference on. IEEE, pp. 31–40.

[10] Chiang, M.-L., Yang, C.-J., Tu, S.-W., 2016. Kernel mechanisms with dynamic task-aware scheduling to reduce resource contention in numa multi-core systems. Journal of Systems and Software 121, 72–87.

[11] Coca, A., Gottsmann, J., Whitaker, F., Rust, A., Currenti, G., Jasim, A., Bunney, S., 2016. Numerical models for ground deformation and gravity changes during volcanic unrest: simulating the hydrothermal system dynamics of a restless caldera. Solid Earth 7 (2), 557.

[12] Dehury, C. K., Sahoo, P. K., 2016. Design and implementation of a novel service management framework for iot devices in cloud. Journal of Systems and Software 119, 149 – 161.

[13] Dongarra, J., Luszczek, P., 2013. Hpc challenge: Design, history, and implementation highlights. Contemporary High Performance Computing: From Petascale Toward Exascale.

[14] Dongarra, J. J., Luszczek, P., 2004. Introduction to the hpccchallenge benchmark suite. Tech. rep., DTIC Document.

[15] El-Gazzar, R., Hustad, E., Olsen, D. H., 2016. Understanding cloud computing adoption issues: A delphi study approach. Journal of Systems and Software 118, 64 – 84.

[16] Filgueira, R., Carretero, J., Singh, D. E., Calderón, A., Náñez, A., 2012. Dynamic-comp: dynamic optimization techniques for mpp parallel applications. The Journal of Supercomputing 59 (1), 361–391.

[17] Gholami, M. F., Daneshgar, F., Low, G., Beydoun, G., 2016. Cloud migration process data survey, evaluation framework, and open challenges. Journal of Systems and Software 120, 31–69.

[18] Gupta, A., Faraboschi, P., Gioachin, F., Kale, L. V., Kaufmann, R., Lee, B., March, V., Milojicic, D., Suen, C. H., 2014. Evaluating and Improving the Performance and Scheduling of HPC Applications in Cloud. IEEE Transactions on Cloud Computing 7161 (1), 1–1.

[19] Gupta, A., Kale, L. V., Gioachin, F., March, V., Suen, C. H., Faraboschi, P., Kaufmann, R., Milojicic, D., Lee, B.-s., 2013. The Who, What, Why and How of High Performance Computing Applications in the Cloud. HP Laboratories.

[20] Gupta, A., Kale, L. V., Milojicic, D., Faraboschi, P., Balle, S. M., 2013. Hpc-aware vm placement in infrastructure clouds. In: International Conference on Cloud Engineering (IC2E). IEEE, pp. 11–20.

[21] Habibollah, W., Hayder, M., Khan, M., Issa, K., Zahrani, S., Shaikh, R., Uwayryedh, A., Tyarkis, T., Baddourah, M., et al., 2003. Parallel reservoir simulation utilizing pc-clusters in massive reservoir simulation models. In: SPE Annual Technical Conference and Exhibition. Society of Petroleum Engineers.

[22] Hair, J. F., Black, W. C., Anderson, R. E., Tatham, R. L., et al., 2006. Multivariate data analysis (Vol. 6). Upper Saddle River, NJ: Pearson Prentice Hall.

[23] Hochstein, L., Basil, V. R., Vishkin, U., Gilbert, J., 2008. A pilot study to compare programming effort for two parallel programming models. Journal of Systems and Software 81 (11), 1920–1930.

[24] Jackson, K. R., Ramakrishnan, L., Muriki, K., Canon, S., Cholia, S., Shalf, J., Wasserman, H. J., Wright, N. J., 2010. Performance analysis of high performance computing applications on the amazon web services
Table 3: Generated synthetic applications and the corresponding execution profiles when executed in a dedicated machine

| Application | Score | Parameters |
|-------------|-------|------------|
| Absolute Value | Score | Parameters |
| S1 | 1635 | 4 | 300 | 1.0 | 0.0 | 0.1 | 25 | 120000 | 5200 | 7000 | 512 | 0 | 22600 |
| S2 | 851 | 61 | 324 | 0.5 | 0.1 | 0.1 | 25 | 90000 | 5200 | 9000 | 1024 | 6 | 22600 |
| S3 | 239 | 41 | 312 | 0.1 | 0.1 | 0.1 | 25 | 40000 | 5200 | 11500 | 2048 | 22 | 22600 |
| S4 | 444 | 444 | 318 | 0.3 | 1.0 | 0.1 | 25 | 7500 | 5200 | 30000 | 512 | 0 | 22600 |
| S5 | 224 | 224 | 324 | 0.1 | 0.5 | 0.1 | 25 | 2700 | 5200 | 39000 | 512 | 21 | 22600 |
| S6 | 797 | 240 | 318 | 0.5 | 0.5 | 0.1 | 25 | 20000 | 5200 | 11800 | 256 | 2 | 22600 |
| S7 | 1597 | 18 | 2892 | 1.0 | 0.0 | 1.0 | 25 | 120000 | 1500 | 7000 | 512 | 0 | 749568 |
| S8 | 890 | 43 | 2832 | 0.3 | 1.0 | 1.0 | 25 | 7500 | 1500 | 30000 | 512 | 0 | 749568 |
| S9 | 224 | 224 | 324 | 0.1 | 0.5 | 0.1 | 25 | 2700 | 1500 | 39000 | 512 | 21 | 749568 |
| S10 | 817 | 241 | 2838 | 0.5 | 0.5 | 1.0 | 25 | 20000 | 1500 | 11800 | 256 | 2 | 749568 |
| S11 | 214 | 214 | 1404 | 0.1 | 0.5 | 0.5 | 25 | 2700 | 1500 | 39000 | 512 | 21 | 150000 |
| S12 | 824 | 239 | 1380 | 0.1 | 0.1 | 0.5 | 25 | 40000 | 1500 | 11800 | 256 | 2 | 150000 |
| S13 | 1575 | 22 | 1392 | 1.0 | 0.0 | 0.5 | 25 | 120000 | 1500 | 7000 | 512 | 0 | 150000 |
| S14 | 220 | 49 | 2910 | 0.1 | 0.1 | 1.0 | 25 | 40000 | 1500 | 11500 | 2048 | 22 | 150000 |
| S15 | 438 | 438 | 2832 | 0.3 | 1.0 | 1.0 | 25 | 7500 | 1500 | 30000 | 512 | 0 | 150000 |
| S16 | 122 | 221 | 1404 | 0.1 | 0.5 | 0.5 | 25 | 2700 | 1500 | 39000 | 512 | 21 | 150000 |
| S17 | 890 | 52 | 1362 | 0.5 | 0.1 | 0.5 | 25 | 90000 | 1500 | 39000 | 512 | 0 | 150000 |
| S18 | 220 | 49 | 2910 | 0.1 | 0.1 | 1.0 | 25 | 40000 | 1500 | 39000 | 512 | 21 | 150000 |

Table 6: Individual profiles of applications used in experiments

| Label | Application | Instance | Processes | Score |
|-------|-------------|----------|-----------|-------|
| MUFITS.I1.P6 | MUFITS | I1 | 6 | SLLC 0.05 | DRAM 0.13 | INN 0.00 |
| MUFITS.I2.P6 | MUFITS | I2 | 6 | SLLC 0.05 | DRAM 0.00 | INN 0.01 |
| HPL.I1.P6 | HPL | I1 | 6 | SLLC 0.03 | DRAM 0.06 | INN 0.02 |
| HPL.I2.P6 | HPL | I2 | 6 | SLLC 0.03 | DRAM 0.06 | INN 0.02 |
| DGEMM.I1.P6 | DGEMM | I1 | 4 | SLLC 0.02 | DRAM 0.04 | INN 0.01 |
| DGEMM.I2.P6 | DGEMM | I2 | 6 | SLLC 0.01 | DRAM 0.02 | INN 0.00 |
| PTRANS.I1.P6 | PTRANS | I1 | 6 | SLLC 0.01 | DRAM 0.02 | INN 0.00 |
| FFT.I1.P4 | FFT | I1 | 4 | SLLC 0.07 | DRAM 0.17 | INN 0.49 |
| FFT.I2.P4 | FFT | I2 | 4 | SLLC 0.07 | DRAM 0.16 | INN 0.52 |

Table 7: Subset of interference experiments

| Co-location | Interference Level | Prediction |
|--------------|-------------------|------------|
| MUFITS.I1.P6xPTRANS.I1.P6 | 44.50% | 39.97% | 4.53% |
| PTRANS.I1.P6xDGEMM.I1.P6 | 5.31% | 12.11% | 6.80% |
| DGEMM.I1.P6xDGEMM.I1.P6 | 7.79% | 2.50% | 5.29% |
| FFT.I1.P4xFFT.I1.P4xFFT.I1.P4 | 49.31% | 40.45% | 8.87% |
| MUFITS.I1.P4xMUFITS.I1.P4xMUFITS.I1.P4 | 22.85% | 11.65% | 11.20% |