Autonomous Learning for Efficient Resource Utilization of Dynamic VM Migration

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ABSTRACT

Dynamic migration of virtual machines on a cluster of physical machines is designed to maximize resource utilization by balancing loads across the cluster. When the utilization of a physical machine is beyond a fixed threshold, the machine is deemed overloaded. A virtual machine is then selected within the overloaded physical machine for migration to a lightly loaded physical machine. Key to such threshold-based VM migration is to determine when to move which VM to what physical machine, since wrong or inadequate decisions can cause unnecessary migrations that would adversely affect the overall performance. We present in this paper a learning framework that autonomously finds and adjusts thresholds at runtime for different computing requirements. Central to our approach is the previous history of migrations and their effects before and after each migration in terms of standard deviation of utilization. We set up an experimental environment that consists of extensive real world benchmarking problems and a cluster of 16 physical machines each of which has on average eight virtual machines. We demonstrate through experimental results that our approach autonomously finds thresholds close to the optimal ones for different computing scenarios and that such varying thresholds yield an optimal number of VM migrations for maximizing resource utilization.

Categories and Subject Descriptors

C.5.5 [Computer System Implementation]: Servers; D.4.8 [Operating Systems]: Performance – *measurements*.

General Terms

Measurement, Performance, Experimentation.

Keywords

Virtualization, Virtual machines, OS migration, Linux cluster, Resource utilization.

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ICS'08, June 7–12, 2008, Island of Kos, Aegean Sea, Greece.

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1. INTRODUCTION

The computational demands of an organization change over time for various reasons. The ability to offer required computing resources under unpredictable growth demands is challenging with the results often being unreliable. A good example is preparing for Monday morning surges. As people start working, there is enormous stress on a multitude of servers and applications. By mid morning the peak will have come and gone. How high the level reaches is unpredictable to some extent. Typically web servers, mail servers, file servers, and database servers are the most heavily taxed systems during these upswings in traffic [1]. To prepare for such a spike in usage, enterprises and organizations are often forced to greatly over-provision computational infrastructure, even though the average utilization of resources maybe typically below 15% - 20% [25].

Research and development efforts conducted to address this utilization problem have led to adaptive infra-structure using resource virtualization [25]. Virtualization techniques have a long history [10] of research, development and implementation, dating back to the IBM System/360 and 370 [7]. Commercial products include VMware [23], Microsoft's Virtual Server [14], and Sun Containers/zones [22]. VMware, a part of EMC, is a virtual machine software suite allowing users to create and execute virtual computers not only on the host OS but more importantly on bare-metal x86 hardware [23]. MS Virtual Server is the virtual machine solution targeted specifically to Windows environment [14]. As built-in virtualization technology in Solaris 10, Sun containers share the same OS images/drivers running on top of the Solaris kernel to provide multiple private-execution environments [22].

Virtualization projects pursued in the open-source community include Xen [2,28], User-mode Linux (UML) [8,9], Bochs [13], Plex86 [16], and others [20]. Xen, apart from XenSource which is now part of Citrix, is a software layer, called para-virtualization, which enables guest operating systems to run on a physical machine [2]. User-Mode Linux (UML) is an application software layer that enables guest Linux operating systems to run on the host Linux operating system. UML, being an application from the host's perspective, requires no modification of the underlying host kernel [8].

When many virtual machines are deployed on a cluster of machines, controlling them can often cause more problems than solutions [18]. Some machines will have many overloaded virtual machines while others do not. To solve its imbalance problem, virtual machine migration methods have been introduced, including Xen Live migration [6], VMware's VMotion [24],

Figure 1. Overview of the system.

Checkpointing [4] such as Berkeley Lab Checkpointing and Restart [12], etc. Studies based on Xen's Live migration explicate the benefits of using runtime VM migration. In particular, the Proactive Fault Tolerance method reported in [15] demonstrates the difference between Xen's Live migration and Stop&Copy-based migration using NAS Parallel Benchmark while Sandpiper [27] illustrates how hot spots can be mitigated using Xen's Live migration in a datacenter environment with high web traffic.

When the utilization of a physical machine is beyond a fixed threshold, the machine is deemed overloaded. A virtual machine within the physical machine will be selected to move to a lightly loaded physical machine. This fixed threshold can become critical to overall performance of the cluster. Not only does finding such thresholds require much time and administrator's continuous intervention but more importantly the resulting threshold may not work for different situations since the computing demands change over time.

It is precisely the purpose of this paper to introduce a framework that autonomously finds and adjusts thresholds at runtime with no human intervention. Central to our approach is the history of migrations along with its impact on performance before and after each migration. For each migration the standard deviation of resource utilization of the cluster is recorded before and after migration. This recording and learning provides a reference point for future decisions. After each learning, the thresholds incrementally approach to the optimal ones.

The paper is organized as follows. Section 2 presents our approach to dynamic migration of virtual machines. Section 3 explains our experimental environment including benchmarking

suites, workload definition, benchmarking methodology, and workload distribution. Section 4 lists experimental results and discusses the results. Section 5 presents performance analysis and the last section concludes our work.

2. DYNAMIC MIGRATION FRAMEWORK

2.1 Overall

The framework shown in Figure 1 consists of a cluster of Linux PCs connected through a network. Each bare-metal machine is comprised of a Linux operating system and virtual machines with our own modules. Vital statistics such as CPU usage are monitored and collected in a predetermined interval by the kernel-level modules. Running on top of the Linux kernel (or host operating system) are multiple User Mode Linux Virtual Machines (UML VM or guest operating systems). The number of UML VMs a machine can accommodate depends on the amount of resources in each machine, in particular memory, CPU speed, and disk. User applications run on UML VMs. A user-level application running on our own kernel modules determines how the currently active VMs are autonomously migrated.

The detailed description of UML VMs and kernel-level modules is illustrated in Figure 2. Each PC consists of VMs, SBUML interface and two to three modules depending on its role. ScrapBook UML (SBUML) [17,19], an extension to UML, provides an OS checkpointing capability that is essential to our dynamic migration framework. With modifications, we seamlessly integrate SBUML into our dynamic migration framework. A PC is designated as the master PC for making decisions on migration while the rest as workers. PC0, the master PC, has three modules of monitoring, learning, and migration

Figure 2. Logical organization. Hmon=host monitor, gmon=guest monitor, mod=module, interf = interface.

while the remaining worker PCs each have two modules, monitoring and migration. Included in each UML VM is a monitoring module for the VM's utilization statistics, not the host's utilization. SBUML interface provides a bridge between the host machine and the guest VMs for checkpointing. Monitoring modules periodically collect utilization statistics for both host and guest machines. The learning module of the master PC checks if any machines are overloaded. If any machine is indeed overloaded, a VM is selected for migration. Migration modules actually move the selected VM to the target PC.

2.2 Monitoring modules

Monitoring modules periodically query OS kernel for CPU and memory usage. Two types of monitoring modules are used: host monitor *hmon* and guest monitor *gmon*. Hmon runs on each host OS to collect the host's usage while gmon on each and every guest OS (VM) to collect guest VM's utilization. Gmon collects statistics from the guest's perspective which is different from the host's.

Host CPU utilization is computed using the "/proc/stat" file of the host OS. Every second the difference is computed and accumulated for a fixed period of time.

At the end of this period, the statistics are averaged and sent to the learning module. Computing guest OS utilization is similar to host utilization. The guest OS utilization is recorded on the log file of the host OS's file system. Writing this allows the host OS to access the guest VM's statistics.

2.3 Learning module

The Learning module determines migration using history matrix along with other information. Each entry of the history matrix consists of the following: standard deviation of CPU utilization before migration, host CPU Utilization, Source Host, Destination Host, and standard deviation of CPU utilization after migration. The learning module works as follows (Figure 3):

Step 1: Obtain CPU utilization for all the hosts and VMs. Find the standard deviation of the host CPU utilization.

Step 2: Check if there is an entry in the matrix that is the same as the current situation in terms of both the current standard deviation and host CPU utilization. If it does exist, check if the standard deviation after migration is less than the current one. If true, it is projected that migration would help. An actual

migration will ensue in Step 4. If there is no such entry in the matrix or the standard deviation after migration is higher, Step 3 will be performed.

Step 3: All the possible migrations are simulated to find the estimated standard deviations after migration. Check if the smallest standard deviation is smaller than the current one. If true, a migration will ensue in Step 4. Otherwise, go back to Step 1 to pick another candidate host machine for migration.

Step 4: An actual migration takes place using the Source Host and the Destination Host determined in Step 2 or 3. A VM with the lowest standard deviation after migration is selected from the host machine for migration. After actual migration, an entry in the history matrix will be added or updated with the current information (standard deviation of CPU utilization before migration, host CPU Utilization, Source Host, Destination Host, and standard deviation of CPU utilization after migration).

2.4 Migration modules

Migration modules move virtual machines. Upon receiving the decision results from the master PC, the migration module of the source PC initiates the first half of migration by creating a snapshot of the selected virtual machine and packing the snapshot, followed by sending to the destination PC. The migration module at the target PC unpacks the snapshot received and resumes the execution of the guest OS.

3. EXPERIMENTAL ENVIRONMENT

3.1 Overview

To test the proposed approach we have set up a cluster of 16 PCs connected through a 100 Mbps switch. Each PC has Pentium 4 2.26 GHz with 1 to 2 GB memory. Linux kernel 2.4.20-6 version is used as the host operating system. Each PC can have up to 16 UML virtual machines each of which uses Linux kernel 2.4.23. The total number of VMs ranges 68 to 136 depending on the configuration. All VMs each have 128 MB of memory allocated. The kernel for VMs consists of 2.4.23 Linux kernel, UML patch, and SBUML patch. SBUML is used for freezing and restoring VMs at runtime. The size of virtual machine file system is typically approximately 100 MB. Table 1 summarizes the key parameters used in the migration framework.

3.2 Benchmark suites

Two benchmark suites of MiBench and SPLASH-2 are used to

Figure 3. Learning procedure.

Table 1. Key parameters for the framework.

Migration thresholds (cpu utilization %)		55%, 65%, 75%, 85%
Learning parameters	CPU standard deviation types	11
	History matrix size	1100 = 11 x 100
Hosts	Monitor collected cpu util & calculated	every second from /proc/stat on hosts
	Monitoring period	20 seconds
Guests	Guest Monitor collect	every second from /proc/stat on guests
	Guest Monitor collecting duration	3 seconds
Number of guests per host		4, 8
Number of guests on the overloaded host		8, 16
Total number of guests		68, 136

test the proposed framework. We selected 30 applications from these suites, all of which run on virtual machines. MiBench [11] is a widely used embedded benchmark suite, which consists of 27 applications. We selected the following 21 applications from MiBench to evaluate the framework: Automotive Class (basicmath, bitcount, qsort, susan), Consumer Class (jpeg, lame, mad, tiff2bw), Network Class (dijkstra, patricia), Office Class (ispell, rsynth, stringsearch), Security Class (blowfish, pgp, rijndael, sha), and Telecomm Class (adpcm, CRC32, FFT, gsm). Each of the above applications requires various input data and parameter settings. It is not practical to list the benchmarking details, except to indicate that we have expended significant time and efforts to develop a set of benchmarking scenarios to closely simulate a realistic computing environment. The second benchmark suite we used is SPLASH-2 (Stanford Parallel Applications for Shared Memory) [26]. The following nine applications are used in our experimentations: ocean contiguous and non-contiguous, cholesky, fft, lu contiguous and non-contiguous, radix, water-n squared, and water-spatial.

Our benchmarking consists of finding three types of workloads: unit, group, and total. Unit workload is defined as the configuration of an application that takes a predefined wallclock execution time within 1-2% tolerance. Group workload is comprised of 100 unit workloads, assembled from various different applications but not necessarily from all 30 applications. Total workload is defined as the number of groups. For our experiments it is set to 10.

3.3 Initial Workload Distribution

The total workload defined above is divided and assigned to each of the 16 PCs. Table 2 lists eight scenarios of how the total workload is assigned to the cluster. In particular, the table shows five different ways of overloading one PC, PC1. The first row indicates that PC1 executes 40% of the total workload while the remaining 15 PCs each execute 4%. The last row, Scenario 5, is an extreme case where PC1 is now assigned 80% of the total

workload while all the other PCs each have merely 1.33% assigned. Again the table shows how one PC is overloaded.

Recall that each PC can have multiple VMs. The workload assigned to each PC is equally assigned to the virtual machines within the PC. This assignment is done in terms of workload units. Now that each and every PC and VM have its work assigned, the cluster starts executing the applications according to the initial distribution. As the execution progresses, the utilization of each PC will change, some will be highly overloaded while some under utilized. VM migrations will ensue to balance the loads across the cluster.

Table 2. Initial workloads assignment for overloading 1 PC.

Scenari	%	PC0	PC1	PC2	...	PC15
1	40%	4	40	4	...	4
2	50%	3.33	50	3.33	...	3.33
...	...	...	...	...	...	...
5	80%	1.33	80	1.33	...	1.33

4. EXPERIMENTAL RESULTS

4.1 No migration vs. migration

We present experimental results in terms of three key parameters: (a) the percentage of workload each PC is initially assigned, (b) the average number of VMs on each PC, and (c) the threshold for migration ranging 55% to 85%. In Table 2, we had only one PC overloaded with 40% of the total amount of work while the rest with 60% (Scenario 1). We now have that particular PC overloaded with $w\%$ of the total workload, where w varies 40% to 80%. 100% work indicates that the overloaded PC is assigned 100% of the total work while others do nothing.

Table 3. Sample completion times in seconds for the total workload under various different scenarios. mig=migration. Initially, 60% of the total workload is assigned to the overloaded PC1.

PC number		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
4 VMs per PC	No mig	408	473	409	415	416	412	418	426	426	430	433	432	460	427	42	433
	Mig (th55)	102	129	123	102	421	120	438	425	426	466	433	433	459	426	42	949
	Mig (th65)	418	108	930	444	120	416	418	116	432	112	436	126	461	433	96	436
	Mig (th75)	418	105	120	425	422	442	115	503	431	110	438	949	461	904	44	116
	Mig (th85)	980	105	421	420	421	421	111	119	915	113	432	431	460	429	42	107
8 VMs per PC	No mig	147	380	150	154	156	165	172	175	177	179	185	188	215	189	19	320
	Mig (th55)	973	907	924	114	116	608	106	867	133	831	119	901	210	129	54	102
	Mig (th65)	145	924	104	563	131	810	932	537	123	130	864	114	134	609	19	118
	Mig (th75)	982	136	107	129	619	714	122	539	128	938	787	745	935	862	19	135
	Mig (th85)	117	136	576	931	103	161	125	132	171	533	121	876	203	661	19	119

Table 3 lists a small portion of the completion times with migration and no migration and for the total workload defined earlier using various different parameter settings. The first row indicates actual PC numbers, *not* the number of PCs. The next row labeled “4 VMs per PC” lists completion times with migration *on* (with thresholds) and *off* for 60% of the total workload initially assigned to 1 PC with four VMs per PC. The third row labeled “8 VMs per PC” lists completion times with eight VMs per PC.

Figure 4 plots the completion times of Table 3 for the 60% initial overload with various thresholds. The x-axis is PC numbers while the y-axis is the completion time in seconds. The thin (cyan) lines indicate the results with no migration while the other lines with migration using various thresholds. The completion times without migration are not consistent as expected since the overloaded machines will take longer to complete the workload while under utilized machines will finish quickly and remain idle. On the other hand, the completion times are consistent across all the machines when migration is turned on.

Consider Figure 4(a), where each PC has four VMs on average. Note that PC1 is overloaded with 60% of the total workload in the beginning. As expected, PC1 took close to 5,000 seconds to complete the workload while all 15 other machines each took only about 400 seconds, leaving PC1 being the critical path. When migration is turned on, however, all the 16 machines

exhibit relatively consistent completion times with no apparent aberrations or critical path since the VM(s) on the overloaded machine were migrated to under utilized machines. The small peaks and valleys are due to the resolution, i.e., the average number of virtual machines in each PC.

When the average number of VMs per PC is increased to eight in Figure 4(b), we obtain results consistent with Figure 4(a) with a few exceptions. As expected, PC1 is still the critical path, taking 4000 seconds to complete while all 15 other machines each took only about 300 seconds. Earlier in Figure 4(a), we found that each of the 15 PCs took approximately 400 seconds. The difference of 100 seconds is due to the fact that a larger number of VMs allows a larger amount of overlapping between computing and communication. In other words, finer granularity of VMs increases an opportunity for overlapping in packing, sending, receiving and resuming among VMs.

We also observe find from the two plots that the fluctuation for 8-VM is smaller than that for 4-VM, except when the threshold is 85%. This high threshold of 85% strongly discourages migrations, resulting in higher discrepancy between those overloaded and under-loaded. We will see later that this high threshold ultimately limits the efficiency of resource utilization.

We have seen in Figure 4 the impact of migration on completion times when 60% of the total workload is initially assigned to one

Figure 4. Comparison of completion times for 60% of the total workload initially assigned to one PC with migration on and off: (a) 4 VMs, (b) 8 VMs per PC.

Figure 5. Overall completion times: (a) 4 VMs, (b) 8 VMs per PC

PC. Figure 5 shows the impact with initial workload ranging 40% to 80%. Again Figure 5(a) is for one PC initially overloaded and each PC with four virtual machines on average while Figure 5(b) is for each PC with eight virtual machines. The x-axis is the percentage of total workload initially assigned to the overloaded PC while the y-axis is the largest completion time. We have plotted in Figure 4 that some PCs finish early while some finish late depending on the machine's load. However, the completion time in Figure 5 is the critical path of a PC that took the longest time. The plot has five curves. The top curves are completion times with no migration while the bottom ones are with migration using the thresholds of 55, 65, 75, and 85%.

The plots clearly indicate that the results with migration are far superior to that with no migration. With no migration we find that the longest completion time by the initially overloaded PC increases as the workload of the overloaded PC increases. When migration is turned on, however, the workloads of the initially overloaded PC have little impact on the overall completion time. In fact the overall completion times with migration appear close to each other because the no-migration results are very large. In what follows, we present the differences.

4.2 Thresholds vs. learning

Figure 6 shows the differences between thresholds and learning. Figure 6(a) is for 4 VMs and (b) for 8 VMs per PC on average. To be more precise, the overloaded PC in Figure 6(a) has *eight* VMs while the remaining 15 PCs each have *four* VMs, resulting in $8 + 4 \times 15 = 68$ VM on the cluster. The x-axis shows the percentage of the total workload on the initially overloaded PC while the y-axis shows execution time in seconds.

The figure shows five curves: four fixed thresholds and learning. It is clear from the figure that varying the threshold results in mixed execution times. Consider when the overloaded PC is initially set to 40% of the total workload. The learning approach and the thresholds of 55, 75 and 85 show similar execution times (approximately 1120 second) while the threshold of 65 performs poorly (close to 1200 seconds). However, this observation does not hold for different initial workloads. When the overloaded PC is initially set to 80% of the total workload, the threshold of 85 shows the worst performance (over 1300 seconds) while the other three shows almost the same execution time.

Figure 6. Execution time in seconds: (a) 4 VMs, (b) 8 VMs on each PC

Figure 7. Number of migrations: (a) 4 VMs, (b) 8 VMs on each PC.

We draw two observations from the figure: First, the fixed threshold method does not yield consistent performance for different computing scenarios. This inconsistent behavior only reinforces our premise that one threshold does not fit all cases. Second, the learning method consistently yields performance close to optimal regardless of the initial workload, except when the initial overloaded PC is set to 50% and 60% of the total workload. These two cases have indicated that the learning method has very little room to maneuver in the history matrix, given the small number of VMs. This observation has led us to double the number of VMs.

We now have on average eight VMs per PC while the overloaded PC has 16 VMs, resulting in $8 \times 15 + 16 = 136$ VMs. Figure 6 (b) shows the results for the four fixed thresholds and learning. Again the x -axis shows the percentage of workload on one particular PC to begin with while the y -axis shows execution times. We find that the performance results are the same or similar to the four fixed thresholds. In other words, one fixed threshold does not fit different computing scenarios. However, we find that the results for learning have improved as we suggested earlier. The learning results are consistently close to optimal except for 80%, which is considered a high threshold that discourages VM migrations. We also find that the 8-VM results show steeper curves than the 4-VMs. The main reason for this steeper curves stems from the very fact that the PC that is initially overloaded is indeed overloaded. Since the PC is overloaded to begin with, migrating 16 VMs takes longer than 8 VMs, resulting in the steeper curves.

5. DISCUSSION

5.1 Number of migrations on performance

Number of VM migrations directly affects performance as each migration entails numerous steps. We wish to find the impact of number of migrations on performance. Figure 7 shows numbers of migrations for various computing scenarios. The x -axis shows the percentage of the total workload on the initially overloaded PC while the y -axis shows number of VM migrations. We observe from the figure that (a) the number of migrations is inversely proportional to thresholds, (b) the change in number of migrations is also inversely proportional to the number of VMs, and (c)

learning yields a moderate number of migrations regardless of the computing scenarios.

Consider the results for Threshold-55 and Threshold-85 in Figure 7(a). The number of migrations for Threshold-55 is three to four times higher than that for Threshold-85. The main reason for this large difference is “easy” migration. Since the threshold is low, migration takes place often and unnecessarily, resulting in higher overhead. On the other hand, the high threshold of 85% severely limits migrations while reducing migration overhead. However, the savings in overhead does not compensate the severe imbalance between physical machines, resulting in lower performance. Learning solves the dilemma. The results show that learning yields a *moderate* number of migrations by finding *right* thresholds for different computing scenarios. This is an indication that the learning approach utilizes resources effectively and efficiently.

The number of VMs affected the number of migrations. When the number of VMs was doubled, the change in the number of migrations has been substantially reduced, as illustrated in Figure 7. For 4-VMs shown in (a), the number of migrations varies substantially. However, for 8-VMs, the variation is small. The difference in variations is in the fact that the smaller number of VMs causes the Ping-Pong problem. When a VM is moved, the receiving PC can be more susceptible to overloading than other PCs, in which case the VM that was just moved may be moved again either back to the original source PC or yet another. This ping-pong behavior thus results in a higher number of migrations. For 8-VMs however, this ping-pong effect is not pronounced since the granularity is smaller and a VM can fit into the receiving PC.

5.2 CPU utilization

CPU utilization indicates how loads are distributed across the cluster. Figure 8 shows CPU utilization for individual PCs. The x -axis is PC numbers while the y -axis is average CPU utilization for the duration of each experiment, where each experiment typically takes tens of minutes to over an hour (See Table 3 for sample completion times).

Figure 8. Sample CPU utilization for the 60% workload initially assigned to PC1: (a) 4 VMs, (b) 8 VMs on each PC.

As expected, no migration shows poor CPU utilization. PC1 which is initially assigned 60% of the total workload maintained 100% utilization throughout while other 15 PCs finished the work early and stayed idle, resulting in close to zero utilization. On the other hand, the thresholds and learning approaches show fairly consistent CPU utilization. Learning exhibits more consistent CPU utilization than other approaches for 4-VMs, except the three PCs (PCs 8, 13 and 14). This aberration is due in part to the fact that the number of VMs is small and there is little room to maneuver. When the number of VMs is doubled, this aberration no longer exists. In general, we find that doubling the number of VMs reduces the average utilization for the given amount of workload. This reduced average utilization further attests to the fact that increasing the number of VMs proportionally increases the efficiency of resource utilization, which will be discussed below.

5.3 Resource utilization efficiency

The results presented above have indicated that the learning method helps find the right thresholds at runtime to increase resource utilization. We wish to identify how efficient the learning approach is compared to the fixed threshold approach and no migration. We define the efficiency for resource utilization E as follows:

$$E = S_{4-VM, no-mig} / S,$$

where Sum S is the resource utilization required to complete the total workload and is defined as $S = \sum U_i * T_i$, where U_i is the total cpu utilization and T_i is the total time taken for PC_{*i*}.

Table 4 lists total resource utilization for individual PCs and Figure 9 plots efficiency. The last row of Table 4 sums all the resource usage for each approach. We find from the table that learning yields the lowest sum (8-VMs) or the second lowest sum (4-VMs) while other approaches vary. For 4-VMs, the difference

Table 4. Resource utilization. The total resource usage for each approach is shown in the last row.

	4 VMs							8 VMs					
	Thr-55	Thr-65	Thr-75	Thr-85	Learn	No-mig		Thr-55	Thr-65	Thr-75	Thr-85	Learn	No-mig
PC0	24405	5112	5355	27783	5767	1210		27740	1540	27241	31893	1801	517
PC1	68469	58339	60175	62061	71296	467443		54647	57233	97983	100635	58216	377669
PC2	36388	27240	21534	4555	4324	1144		17981	26447	27469	9976	1356	507
PC3	25172	4942	5160	4733	4545	1199		29754	10151	28283	12122	29615	526
PC4	4341	28775	4769	4694	4596	1178		27610	37904	10486	27325	25908	514
PC5	39446	4159	18370	4442	4324	1119		10762	13082	12124	1478	19242	567
PC6	17380	16503	53638	54193	4363	1156		28468	25816	28889	40273	29791	591
PC7	7047	51546	7294	52333	4713	1235		13118	9892	9896	30472	1619	601
PC8	4241	12537	4883	27148	54006	1213		27559	28333	29776	3777	35318	601
PC9	8501	54206	54355	52639	4705	1244		12091	30600	25514	8976	16885	607
PC10	4369	4630	5057	4644	4582	1231		27798	12839	12080	25284	27268	629
PC11	4245	32549	28233	4564	4568	1206		11974	29824	11525	10661	12149	633
PC12	8294	5629	5850	5709	5650	1557		2348	32821	15390	2091	6035	903
PC13	3771	4386	27753	4115	48852	1094		29683	10225	12835	10411	1738	620
PC14	3731	25879	5578	4052	51427	1048		10576	2140	2143	2169	32161	1039
PC15	25737	4547	57421	53443	24540	1535		38011	39867	40317	35300	7060	2070
Sum S	285535	340980	365422	371109	302257	485811		370120	368712	391950	352843	306160	388593

between the lowest (285535) and learning (302257) is 0.5%, which is small enough to be considered as noise. Again the main reason for this low total utilization is due to the fact that the loads are equally distributed across the cluster. Figure 9 summarizes our study: learning thresholds at runtime gives the highest or close to the highest efficiency for resource utilization.

Figure 9. Resource utilization efficiency.

6. CONCLUSIONS

Dynamic migration of virtual machines is designed to maximize resource utilization by balancing loads across the cluster. In this paper, we have presented a learning framework that autonomously finds and adjusts the thresholds for determining candidate VMs for migration. We have set up an experimental environment with a cluster of 16 PCs. Each PC has on average 4 to 8 User Mode Linux (UML) VMs, resulting in the total of 68 to 136 VMs depending on experimental settings. Each VM ran two suites of 30 benchmark programs that include applications for daily computing. Key to our approach is the learning module that autonomously finds and adjusts the thresholds for selecting source VMs and destination PCs using migration history and standard deviation of the CPU utilization of VMs.

We have performed numerous experimentations with three key parameters. First, the percentage of workload each PC is initially assigned varied from 40% to 80% of the total workload. Second, the average number of VMs on each PC varied four to eight. Third, the threshold for migration varied 55% to 85%. Experimental results have demonstrated that (a) the overall performance with migration was far superior to that with no migration; (b) the learning approach consistently performed better than the threshold approach. We have found that learning yields *moderate* but consistent number of migrations by finding *right* thresholds for different computing scenarios. On the other hand, the fixed-threshold approach has yielded varying number of migrations for different computing scenarios, resulting in overall performance degradation; (c) the learning approach has yielded the highest or second highest efficiency in resource utilization among all the experimentations. In summary, we find that learning thresholds at runtime has indeed helped maximize the limited resources.

7. REFERENCES

- [1] V. Almeida, R. Riedi, D. Menasce, W. Meira, F. Ribeiro, R. Fonseca, Characterizing and modeling robot workload on e-business sites, in *Proc. ACM SIG METRICS*, June 2001.
- [2] P. Barham, B. Dragovic, K. Fraser, S. Hand, T. Harris, A. Ho, R. Neugebauer, I. Pratt, and A. Warfield, Xen and the art of virtualization, in *Proceedings of the 19th ACM Symposium on Operating Systems Principles*, October, 2003, pp. 164 - 177.
- [3] T. L. Borden, J. P. Hennessy, J. W. Rymarczyk, Multiple operating systems on one processor complex, *IBM Systems Journal*, 28(1), 1989.
- [4] The Home of Checkpointing Packages, <http://www.checkpointing.org>
- [5] P. M. Chen, B. D. Noble, When virtual is better than real, in *Proceedings of the 2001 Workshop on Hot Topics in Operating Systems (HotOS-VIII)*, May 2001.
- [6] C. Clark, K. Fraser, S. Hand, J. G. Hansen, E. Jul, C. Limpach, I. Pratt, and A. Warfield, Live Migration of Virtual Machines, in *Proceedings of the 2nd Symposium on Networked Systems Design and Implementation (NSDI)*, May 2005.
- [7] R. J. Creasy, The Origin of the VM/370 Time-Sharing System, *IBM Journal of Research and Development*, September 1981, pp. 483 - 490.
- [8] J. Dike, A user-mode port of the Linux kernel, in *Proceedings of the 4th USENIX Annual Linux Showcase and Conference*, Atlanta, GA, USA, October 2000.
- [9] J. Dike, The User-mode Linux Kernel Home Page, <http://user-mode-linux.sourceforge.net/>.
- [10] R. P. Goldberg, Survey of Virtual Machine Research, *IEEE Computer Magazine*, vol. 7, no. 6, June 1974, pp. 34 - 45.
- [11] M. R. Guthaus, J. S. Ringenberg, D. Ernst, T. M. Austin, T. Mudge, and R. B. Brown, MiBench: A free, commercially representative embedded benchmark suite, in *IEEE 4th Annual Workshop on Workload Characterization*, December 2001.
- [12] P. H. Hargrove, J. C. Duell, Berkeley Lab Checkpoint/Restart (BLCR) for Linux Clusters, in *Proceedings of SciDAC 2006*, June 2006.
- [13] K. Lawton et al., Bochs IA-32 Emulator Project, <http://bochs.sourceforge.net>
- [14] Microsoft Corporation, Virtual Server 2005 R2 Technical Overview, <http://download.microsoft.com/download/5/5/3/55321426-cb43-4672-9123-74ca3af6911d/VS2005TechWP.doc>, December 2005.
- [15] A. Nagarajan, F. Mueller, C. Engelmann, and S. L. Scott, Proactive fault tolerance for HPC with Xen virtualization, in *Proceedings of the 21st ACM International Conference on Supercomputing (ICS) 2007*, Seattle, WA, USA, June 2007.
- [16] Plex86 x86 Virtual Machine Project, <http://plex86.sourceforge.net>
- [17] R. Potter, One-Click Distribution of Preconfigured Linux Runtime State, in *WIP Session of the 3rd Virtual Machine*

Research and Technology Symposium (VM04), San Jose, CA, USA, May 2004.

- [18] C. P. Sapuntzakis, R. Chandra, B. Pfaff, J. Chow, M. S. Lam, and M. Rosenblum, Optimizing the Migration of Virtual Computers, in *Proceedings of the 5th Operating Systems Design and Implementation*, Boston, MA, USA, December 2002, pp 377 - 390.
- [19] SBUML, ScrapBook for User-Mode Linux, <http://sbuml.sourceforge.net/>.
- [20] A. Singh, An Introduction to Virtualization, <http://www.kernelthread.com/publications/virtualization>.
- [21] J. E. Smith, R. Nair, Virtual Machines: Versatile Platforms For Systems and Processes, Morgan Kaufmann, San Francisco, CA, USA, 2005.
- [22] Sun Containers: Server Virtualization and Manageability, A Technical White Paper, http://www.sun.com/software/whitepapers/solaris10/grid_containers.pdf, Sun Microsystems, September 2004.
- [23] VMware ESX Server, <http://www.vmware.com/products/vi/esx/>, VMware, Inc.
- [24] VMware VirtualCenter, <http://www.vmware.com/products/vi/vc/>, VMware, Inc.
- [25] M. Welsh, D. Culler, Adaptive overload control for busy internet servers, in *Proceedings of the 4th USENIX Conference on Internet Technologies and Systems*, Seattle, WA, USA, March 2003.
- [26] S. C. Woo, M. Ohara, E. Torrie, J. P. Singh, and A. Gupta, The SPLASH-2 Programs: Characterization and Methodological Considerations, in *Proceedings of the 22nd International Symposium on Computer Architecture*, pp. 24-36, Santa Margherita Ligure, Italy, June 1995.
- [27] T. Wood, P. Shenoy, A. Venkataramani, and M. Yousif, Black-box and gray-box strategies for virtual machine migration, in *Proceedings of the 4th Usenix Symposium on Networked System Design and Implementation (NSDI)*, Cambridge, MA, April 2007.
- [28] The Xen Virtual Machine Monitor, <http://www.cl.cam.ac.uk/Research/SRG/netos/xen/>, University of Cambridge Computer Laboratory.