Virtualization in the Private Cloud: State of the Practice

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***Abstract*—Virtualization has become a mainstream technology that allows efficient and safe resource sharing in data centers. In this paper, we present a large scale workload characterization study of 90K virtual machines hosted on 8K physical servers, across several geographically distributed corporate data centers of a major service provider. The study focuses on 19 days of operation and focuses on the state of the practice, i.e., how virtual machines are deployed across different physical resources with an emphasis on processors and memory, focusing on resource sharing and usage of physical resources, virtual machine life cycles, and migration patterns and their frequencies. This paper illustrates that indeed there is a huge tendency in over-provisioning CPU and memory resources while certain virtualization features (e.g., migration and collocation) are used rather conservatively, showing that there is significant room for the development of policies that aim to reduce operational costs in data centers.**

***Index Terms*—Data centers, virtualization, private cloud, workload characterization.**

I. Introduction

MANAGEMENT of virtual machines (VMs), such as provisioning, de-provisioning, and migration, is central to the operation of data centers, which constitute contemporary cloud environments where applications execute in the form of VM instances. Naturally, each VM instance varies in terms of its required virtual resources. In addition, throughout its lifetime, a VM may be collocated on the same physical host with a different number of other VMs. VMs can be easily suspended, restarted, and migrated on different hardware to better meet performance objectives from the points of view of the individual applications and of the data center.

A data center's ability to gracefully deal with persistent workload fluctuations strongly depends on its ability to reconfigure and migrate VMs. There has been a lot of research into the costs of dynamic reconfiguration, consolidation, and migration [1]–[3], but most experimental work reports on small-scale and easily controllable hardware environments. Yet, there is no clear view of the current state-of-the-practice — how production data centers are used by their tenants and what are their common VM characteristics, resource sharing, and migration patterns.

In this paper, we aim to fill this gap by providing a detailed characterization study of VM usage in corporate data centers in the private cloud of a major provider. Our objective is to provide a better understanding of how virtualization is deployed and specifically the general conditions that drive VM management policies that trigger migration and VM consolidation.

We inspect multiple corporate data centers used by more than three hundred customers from a variety of corporations, including banking, industrial, automotive, retail, and media industries, geographically dispersed across different countries and continents. The trace data focus on a specific time window of 19 days ranging from September 1, 2012 to September 19, 2012, of several data centers, serving more than 90 VMs hosted on over 8K physical servers. This data set provides insights into a broad range of both physical and virtual hardware configurations running a diversity of operating systems and applications. The data centers considered here are within a private cloud, i.e., their tenants and applications are stable. The broad variety of hardware that populates the data centers coupled with the vast number of VMs allows to gain insights into physical hardware usage, VM routine usage, VM on/off activity, as well as migration and consolidation patterns. Note that the data centers of our study are hosted by different entities of the provider, so migration and consolidation policies may not be the same across data centers. Yet, the nature of the data allows us to provide a bird's eye view of the degree of consolidation reached in data centers as well as the overall volume of VM migrations, provisioning, and de-provisioning. Beyond the overall view, we also focus on how resource allocation and utilization are affected by different VM management policies, in terms of long-term and instantaneous trends (i.e., within the allowable time granularity of our measurements).

Our findings can be summarized as follows. Among the various resources, CPU is commonly over-committed while this happens rarely for memory. Up times of VMs are long, with a significant percentage of them to be always on, throughout the 19-day time period. VM commissioning and decommissioning

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follow specific time patterns and this activity is highest during midnight, ditto for VM migration. There is a strong tendency to not migrate VMs and even if migration happens, it only involves a restricted set of physical servers with the same hardware characteristics. Migrations appear to aim at moving VMs to physical boxes with smaller resource utilizations than the source ones, pointing at improved load balancing and better performance.

This paper is organized as follows. Section II presents an overview of the collected data. Characterizations of VM virtual resource allocation, consolidation, life cycle, and migration are summarized in Sections III, IV-A–IV-C, respectively. Sections V and VI focus on how resource management policies affect resource allocation and utilization, respectively. In Section VII we give an overview of lessons learned from the VM management analysis. Section VIII positions this paper within other works. Conclusions and future work are given in Section IX.

II. Data Collection

We survey ~90K VMs, hosted on ~8K physical servers from different data centers in the world, serving over 300 corporate customers over a 19 day period starting September 1, 2012. Thanks to these sheer numbers, we can deduce meaningful statistics. These systems are used by different industries and are based on various operating systems. The virtualization technologies used are from major vendors, such as VMware and IBM.

Due to the nature of the trace data available to us, our study has some limitations. Although the trace data identifies unique VMs (via a unique VM id), we are unaware of the exact applications each VM runs due to business confidentiality. We are also not aware of the response time of each VM at the transaction level (if the application is transaction-based) but we are aware of the end-to-end time of an application. In addition, the trace data is only collected in 15-minute periods, i.e., this is the finest available data granularity.

While a 15-minute sampling interval may be considered relatively long and may compromise the completeness of the data set with respect to very frequent events, we argue that it actually has a negligible effect given the typical liveness and migration characteristics of most VMs in this data set. Our evaluation suggests that provisioning and de-provisioning as well as migrating are much less frequent than data sampling in the vast majority of cases. For a more detailed description of the trace data and data center workload characteristics (but without considering the VM perspective), we direct the interested reader to our previous work on the same data set that focused on evolution of data center resource demands across a two-year period [4] and also on seasonal utilization patterns to enhance autonomic resource allocation policies [5].

For the purpose of the work presented in this paper we collect two types of virtualization statistics, namely on *virtual resource provisioning* and on *VM deployment*. Virtual resource provisioning focuses on the amount of virtual resources assigned to each VM. VM deployment focuses on how physical resources are shared by VMs on a physical server. We

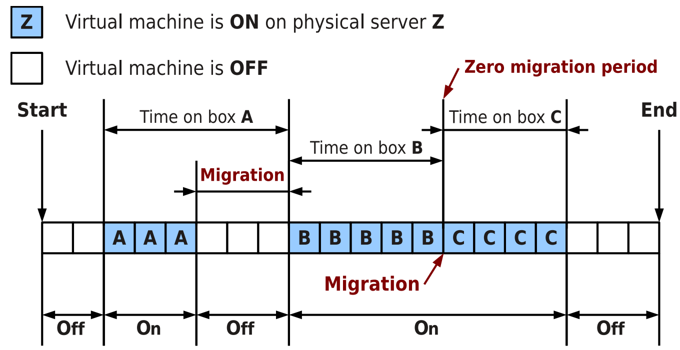


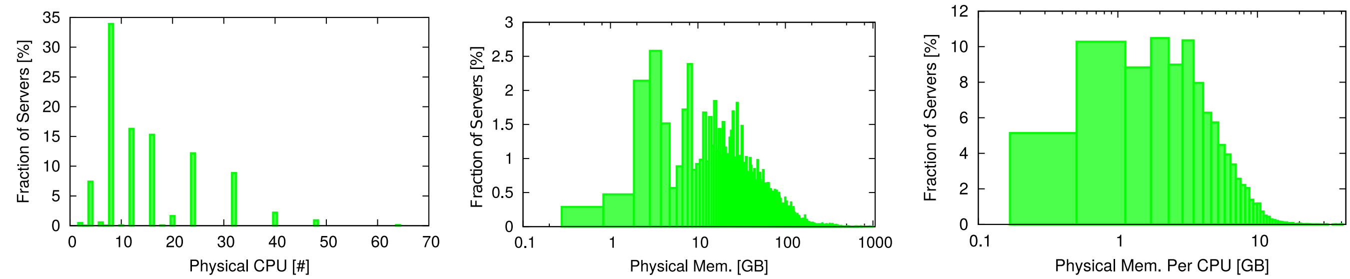
Fig. 1. The definition of VM on, off, host and migration times.

concentrate on the number of VMs and on their virtual CPU and virtual memory capacity demands, and how those are shared on their physical counterparts where the VMs are deployed. Throughout this paper, we use the terms *server* and *host* to denote a VM's physical counterpart. We also use the generic terms *processor* and *CPU* interchangeably to denote a thread slot visible to the operating system.

A physical server equipped with multiple physical CPUs (pCPU) and sufficient physical system memory (pMEM) hosts multiple VMs. Each VM in turn is configured with multiple virtual CPUs (vCPU) and virtual system memory (vMEM) of a certain size. The total number of vCPUs is independent of the number of pCPUs on a physical server. A vCPU can use only up to one pCPU at a time, whereas a pCPU *may* be shared by multiple vCPUs. Similarly, the total size of vMEM used by the VMs is independent of the available pMEM.

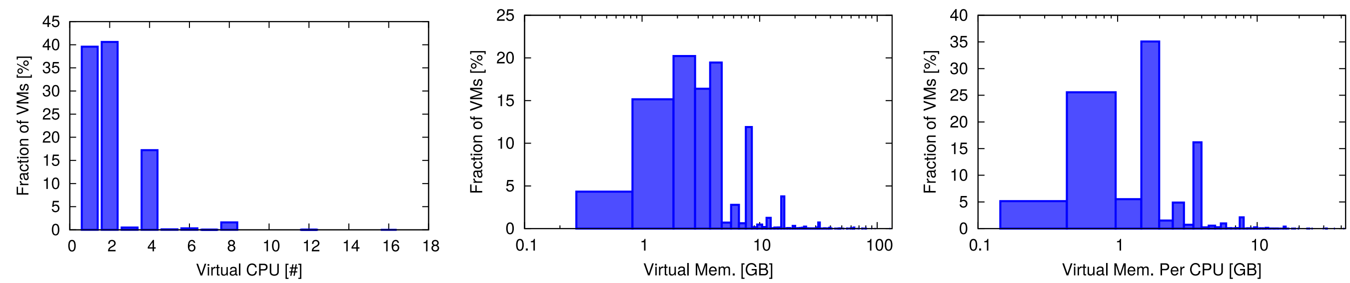
VM deployment may be static or dynamic, i.e., a VM may be bound on a physical server throughout its lifetime or not. We focus on the dynamic handling of the VMs over the entire period by looking at VM life cycles (on/off patterns) and VM migrations. We consider a VM on, if the VM is running and its activity is traced during the 15-minute sampling interval; we consider the VM off otherwise. Naturally, on/off periods and migration can be intertwined: i.e., a VM can be turned off and then turned on at a different physical host. In such cases, we consider that both a VM life cycle and migration occur. Live migrations are also possible: i.e., a VM migration without the VM being suspended or turned off.

For a better understanding on how and what we measure, see Figure 1. The figure illustrates an example of VM dynamic behavior over time. The VM first runs on server A, then B, then C, i.e., two migrations occurred. When the VM is migrated from server A to server B, it is also turned off during three time intervals. Migration from B to C has no gaps, either because of live migration or because the off time is hidden by the sampling interval. Based on this example we further illustrate the four basic time intervals we measure: the on and off times (i.e., the sum of all consecutive time periods in which the VM is in the same on or off state), the host time (i.e., the time spent by the VM on the same physical server irrespective of being on or off), and the migration time (i.e., the off time between changing physical hosts) which can be zero.



(a) Number of pCPUs per server (b) Size of pMEM per server (c) pMEM / pCPU ratio

Fig. 2. Physical resources available on today's servers: (a) number of CPUs, (b) memory size [GB], and (c) ratio of memory (size) per CPU. Note the log-scale on the x-axis for (b) and (c), to better illustrate the higher densities that are associated with smaller memory requirements.



(a) Number of vCPUs per VM (b) Size of vMEM per VM (c) The vMEM/vCPU ratio

Fig. 3. Allocation of virtual resources per VM: (a) number of vCPUs of a VM, (b) memory size of a VM, and (c) ratio of memory size per vCPU. Note the log-scale on the x-axis for (b) and (c), to better illustrate the higher densities that are associated with smaller memory requirements.

III. Resource Allocation

In this section, we give an overview of the degree of sharing in physical and virtual machines. We also give an overview of the common resource configurations at the physical servers as those are provisioned to the VMs.

A. Representative Physical Machines

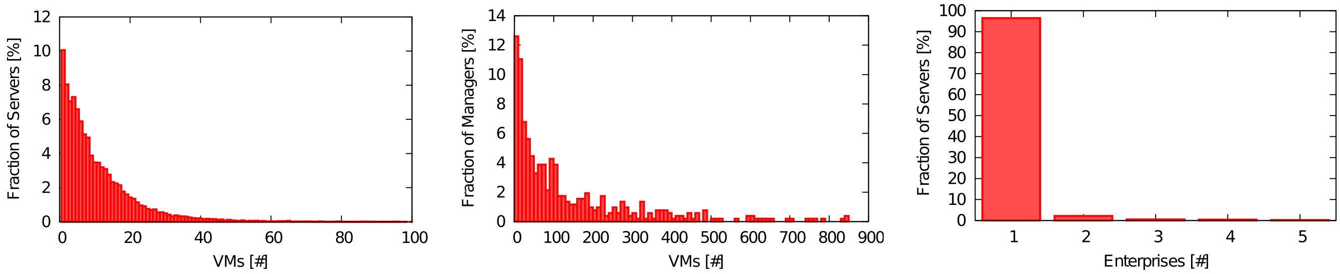
In this subsection, we present statistics on the physical resources, and in particular on processors and memory, that are available in today's servers. In Figure 2, we give an overview of physical resources available. Figure 2(a) shows the histogram of pCPUs per server. The histogram reflects the availability of commercial configurations. In the most common case (i.e., 34.5%) servers have eight pCPUs. Other common configurations are 12, 16 and 32 pCPUs. The pMEM configurations have a much wider range, see Figure 2(b). The highest peaks in the histogram are between 2 GB and 50 GB and account for 56% of servers. Overall, servers have abundant resources with an average of 14.95 pCPUs and 60.6 GB of pMEM. Some high-end machines exist even at 64 pCPUs and 1 TB of pMEM. In addition, there is a non negligible portion of "resource limited" servers with 4 pCPUs and less than 2 GB of pMEM. Figure 2(c) gives a sense on how balanced the physical servers are in terms of processors and memory by presenting the histogram of the ratio between these two resources. The average value is 3.98 GB memory per CPU.

The main message of Figure 2 is that today's servers have very powerful computational capacity (on average 15.95 pCPUs) and a reasonable size of memory (on average 60.6 GB of pMEM) making room for resource sharing by VMs (on average 10.8 VMs per server). The histograms depicted in Figure 2 also allow to identify representative server configurations useful for system and resource allocation studies.

B. Representative VM Configuration

Knowing that many VMs are co-located on a physical server, a natural question to ask is if they share resources equally, i.e., how VMs are provisioned in terms of virtual resources. Figure 3(a) illustrates that VMs use mostly a small number of vCPUs. Most VMs have either 1 vCPU (39.5%), 2 vCPUs (40.6%), or 4 vCPUs (17.2%).

Similar observations hold for the vMEM size (see Figure 3(b)): most VMs (87.2%) have between 1 and 9 GB of vMEM with specific peaks around 2, 4, and 8 GB. On Amazon EC2 five instance type exists: micro, small, medium, large, and x-large. Of those, micro and small have 1 vCPU while the rest of instance types have more than 2 vCPUs [6]. vMEM ranges are from 0.615 GB (for micro) up to 244 (for the more "rare" 8x-large cases), while small and large are within a range of 3 to 15 GB. Indeed, our data confirms that the most popular VM configurations in our trace data correspond to those of EC2. Finally, as indicated by the different histogram shape in Figure 3(c), the memory/processor ratio is scaled down: on average 2.3 GB of vMEM per vCPU. Overall, our key observation is that VMs are "smaller" than physical machines, in terms of number of CPUs and memory. In addition, as reported in the previous subsection, the daily averages and percentile values are remarkably stable across time. One can use these statistics to size VM resources, especially within cloud solutions.



(a) Number of VMs per server (b) Number of VMs per manager (c) Number of enterprises per server

Fig. 4. Statistics related to VM consolidation: (a) number of VMs hosted on physical servers, (b) number of VMs under a managing unit, and (c) number of different enterprises running VMs in a single physical server.

IV. VM Management

A. Consolidation

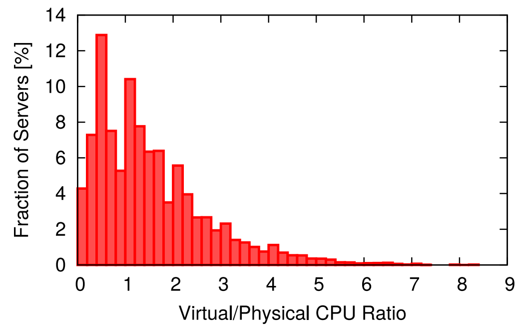
One of the first issues of interest is the consolidation levels on the various physical machines, see Figure 4. Figure 4(a) shows the discrete data histogram of the empirical density of the number of VMs per physical server. The figure shows that 10% of servers host only one VM, i.e., there is no consolidation. 90% of servers host at least two VMs. The average number of VMs hosted on a physical server is 10.8 but this average can be deceiving. Indeed, the CDF counterpart of Figure 4(a) (not reported here due to lack of space), shows that the 95th percentile of VM consolidation is 31.

For completeness, we present two more histograms. The first one is the histogram of the number of VMs handled by the same management unit (i.e., an external entity used to monitor and deploy the VMs, such as *vsphere* from VMware), see Figure 4(b). In general, a manager handles many VMs, 173.3 VMs on the average. Since central VM managers can become the bottleneck, such information can be useful for capacity planning of management units.

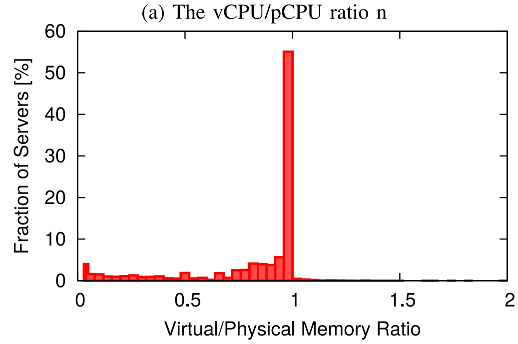
Figure 4(c) depicts the histogram of the number of different customers sharing the same physical server. We see that there is almost no flexibility here: 96.5% of servers host VMs all belonging to the same customer. This further confirms that the statistics presented in this paper are mostly from private clouds.

In this subsection, we present how virtual processors, physical processors, and memory are related. We start with how vCPUs compete for pCPUs on a physical server. Figure 5(a) shows the histogram of the ratio between the total number of all vCPUs from all VMs and the number of pCPUs of the underlying hosting physical server. If such a ratio is less than 1, then vCPUs are likely not able to "stress" pCPUs: i.e., the server is under-populated. Ratios greater than one are necessary (but not sufficient) conditions for processor resource contention. Roughly 35.2% of servers are under-populated, 4.3% even with ratios lower than 0.1, while the rest of the servers have ratios greater than 1 and up to 8.25. Overall, the average is 1.56 vCPUs per pCPU. This is not surprising, considering that efficient physical resource sharing is in fact the purpose of virtualization.

Next, we study how pMEM is shared among the vMEMs allocated to each VM. To this end, we compute the ratio between the sum of all vMEMs and the pMEM of the



(a) The vCPU/pCPU ratio n



(b) The vMEM/pMEM ratio

Fig. 5. Comparison between the amount of virtual and physical resources per physical server. Note the log-scale on the x-axis for (b) to better illustrate the higher densities that are associated with smaller memory requirements.

underlying physical server. Figure 5(b) depicts such ratios and illustrates that it is very rare for VMs to request more than the available pMEM.

We summarize the statistics discussed in this section as follows. Consolidation of multiple vCPUs on pCPUs is prevailing, as expected, especially considering the main motivation for virtualization – efficient consolidation of resources. The degree of over subscription is roughly at 50%, indicated by the mean value of vCPU/pCPU. On the opposite, memory is never over committed, i.e., the total vMEM requested is just slightly less than the pMEM of the hosting server. Resource sharing is more conservative for memory than for CPU.

B. Life Cycle of VMs

The ease of commissioning and decommissioning VMs, together with the promise of performance isolation, contribute to the popularity of using VMs in data centers. Since the

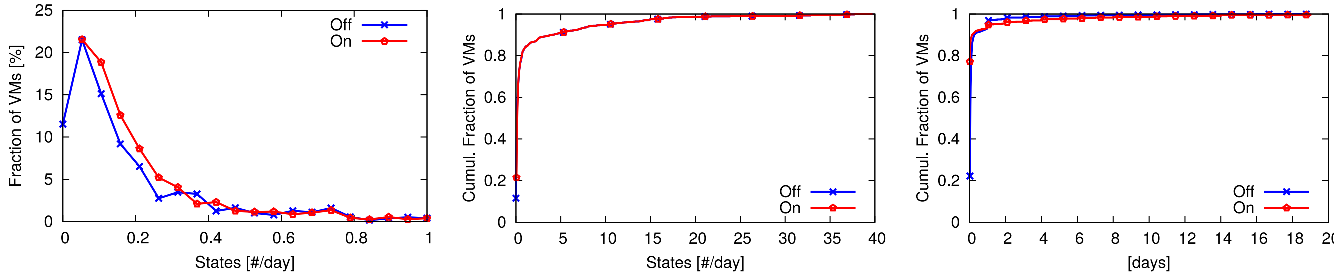


Fig. 6. Statistics related to VM on/off cycles: (a)(b) daily frequency, (c) duration of on/off periods.

trace data come from data centers within privately administered clouds, our observations are bound to the private clouds only. In this section we focus on the frequencies at which the VMs are turned on and off, the durations of the on/off times, and whether the VMs are bound to the physical servers where they execute.

1) VM On/Off Frequencies and Times: We start by reporting on the number of on and off states for each VM across the observation period of 19 days. Naturally the numbers of on and off states are tightly related, since an off (on) state is always going to be followed by an on (off) state, respectively. Provided that we observe each VM over a fixed time interval, the number of off states is at most the number of on states ± 1, depending on whether we observe a leading or trailing off state without a corresponding on state. Figure 6(a) presents the frequencies of on and off states during the 19-day observation period, computed over the set of all VMs. As expected, the lines are almost overlapping with few deviations (e.g., the starting points of the two curves). In the rest of this section we only comment on the frequency of the off states.

One can immediately see that most of the frequency mass is located at the beginning. To better illustrate the results, Figure 6(a) shows only the initial part of the PDF, while Figure 6(b) shows the complete cumulative distribution function (CDF), including its tail. 11% of VMs have *zero* observed off states, i.e., these VMs are continuously operating during the entire 19-day interval. The absence of off samples suggests that these VMs have never been turned off, therefore we treat them as if they are turned on once. Furthermore, 23% of VMs have only one observed off state throughout the 19-day interval or, estimating based on the observation period, only 0.053 off states per day. For the remaining VMs, the density functions rapidly decay into a long tail which extends almost to the maximum possible value given by the 15-minute sampling interval, i.e., 48 times per day. This suggests that some VMs stay on for one sampling interval and off for the subsequent one throughout the whole observation period. Figure 6(b) shows the complete CDF that illustrates the presence of a long tail, i.e., there are at least 2% of cases where the number of on/off states per day is more than 20. Note also that the two CDF curves nearly completely overlap.

Next we focus on how long a VM stays in either the on or off state. We call these durations "on/off times". Figure 6(c) presents the CDFs of the on and off times across all VMs. Again, the line corresponding to the off state is either roughly overlapping or above the line corresponding to the on state, suggesting that off periods are in general shorter than on periods. In general, we see that for almost 90% of the VMs the on or off times are less than a portion of the day, while a small percentage corresponds to very long on/off durations.

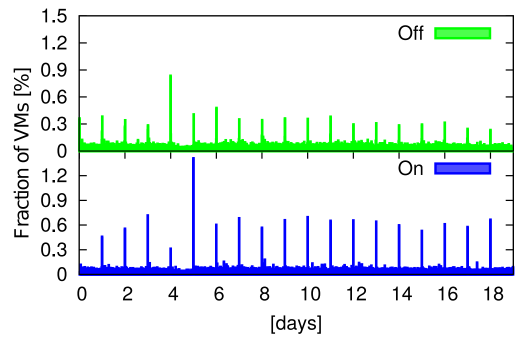
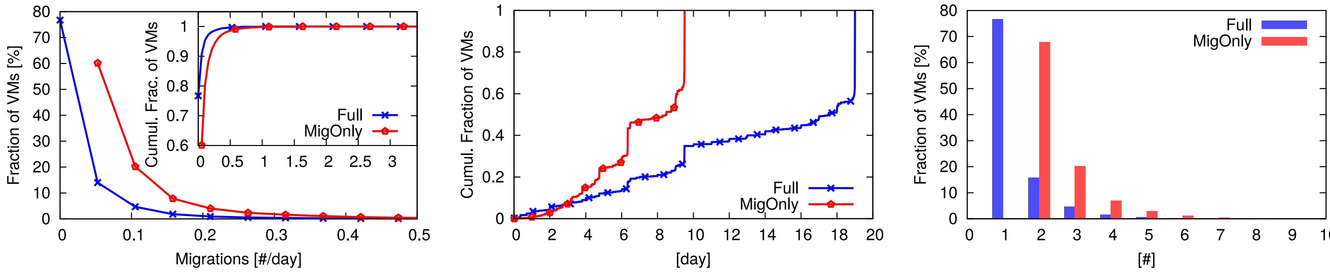


Fig. 7. Fraction of VMs that are turned on and off at specific time stamps, across the entire observation period.

2) More on VM On/Off Durations: Here we provide information about the specific times when VMs are turned on and off. Figure 7 presents the empirical frequencies of the fraction of VMs that are turned on and off as a function of the time of the day across the entire 19-day period. For each time period, two bins are reported, one that corresponds to on and one that corresponds to off. Graphs are stacked on top of each other in order to illustrate the relationship of on and off frequencies. Remarkably, there is a strong repeating pattern on the frequencies of on/off time periods, i.e., the time stamps at which VMs are switched on are repetitive, featuring a daily spike. In the rest of the time periods the fraction of VMs that are turned on or off is more of less stable. Looking more closely at the numbers, 12% of all VMs in the entire time period are started at midnight, while almost 6% of VMs are shut down in the same time period and 3% right before this time. Such repeatable patterns clearly point to routine VM deployment or perhaps maintenance work.

C. VM Migration

In this section we focus on one of the most important features of virtualization: migration. Migration plays an indispensable role in bridging two key aspects of virtualization: server consolidation and scalable resource provisioning.



(a) PDF and CDF (inlet): Migration frequency (b) CDF: Inter-migration time (c) PDF: Number of unique servers visited

Fig. 8. Statistics about VM migration: (a) how often it happens in a day, (b) how long does it take between migrations, and (c) how many different servers a VM visits.

Most of existing migration studies are done within controlled environments of small scale, for more details see Section VIII. Here, our data allows to provide the big picture on current migration practices in the private cloud. First, we focus on the frequency of VM migration, and how much this frequency varies from VM to VM. Second, we are interested in isolating observable migration patterns, trying to see whether VMs migrate regularly. Finally, we also report on how many physical servers the VMs migrate on. In this section we concentrate on the large-scale characteristics of VM migration, without attempting to evaluate its performance impacts.

1) Migration Frequency and Inter-Migration Times: In the following, we split the data into two sets and draw the empirical distribution functions for (i) the entire set of VMs, which we call the *full set*, and (ii) the set of VMs that migrated at least once within the 19 days, referred as *migration-only set*.

Figure 8(a) shows the frequency of VM migration, i.e., how often a VM migrates between physical servers. The main plot zooms on the initial part of the PDF across VMs. This illustrates the fact that most VMs are unlikely to migrate: 78% of them never migrated throughout the whole 19 days, i.e., the migration frequency was equal to zero. However, as shown in the inlet of Figure 8(a), the right tail of the CDF also includes a few VMs that migrated more than three times per day.

Figure 8(b) shows the cumulative frequencies of the average residence time of a VM on a physical server before migrating to another server. This is an alternative representation of the results shown in Figure 8(a), confirming that most VMs exhibit relatively long inter-migration times. In particular, only about 3% of VMs belonging to the migration-only set have inter-migration times of 2 days or less. There are four peaks of increasing intensity at 3.8, 4.8, 6.3 and 9.5 days which are influenced by the length of the observation period and correspond to fractions of 19 days. The full set is skewed even more towards longer inter-migration times, due to the considerable number of VMs that never migrate and remain active for the whole 19 days. This can be seen from the big jump at the end of the CDF. Since the full set includes the migration-only set, the full set's density function exhibits the same jumps scaled in intensity as the one corresponding to the migration-only set.

The main message is that most VMs (78%) never migrate. Furthermore Figure 8(a) and Figure 8(b) both point towards rather long periods between migrations. In particular the highest peaks are either just slightly shorter than a week, i.e., 6.3 days for 10% of migrating VMs, or just slightly longer than a week, i.e., 9.5 days for 28% of migrating VMs.

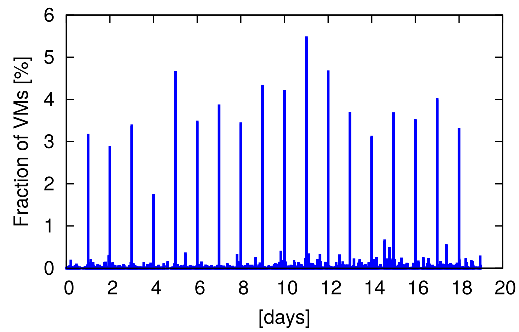


Fig. 9. Fraction of migrating VMs across the entire observation period.

2) Migration Timings and Patterns: Herein, we focus on VMs experiencing migrations, particularly their timings of occupancies and spatial patterns on underlying servers. Figure 9 reports on the fraction of VMs that migrate across the entire 19 day period. The figure shows a strong repetitive pattern: most migrations occur at specific time stamps, that appear to repeat across the entire 19-day period. Looking at the same information but as an aggregate within 24 hours, it is clear that almost 70% of all VM migrations occur at midnight.

Regarding the spatial patterns of migration, i.e., *where* VMs migrate, we look at (i) the number of distinct physical servers visited and at (ii) the probability of transitions among those servers. Figure 8(c) shows the PDF of the number of distinct physical hosts visited by a VM over the 19 days. A value of one means that the VM stayed on the same physical host for all 19 days. Again, we observe that 78% of VMs do not migrate, which is consistent with our previous results. Even considering the *migration only* set, mostly the set of physical servers visited by a VM is relatively small: 68% of VMs visit only two servers. Table I summarizes statistics for migration frequencies, intermigration times, and numbers of unique servers visited.

Table II gives an overview of the overall migration pattern: where each row (column) represents the origin (destination) host during migration and the associated numerical value reflects the transition probability from the origin to the destination. Such a transition probability set is computed for each VM and the servers are labeled according to the order of their

TABLE I
STATISTICS FOR MIGRATION: FREQUENCY, INTER-MIGRATION TIMES, AND NUMBER OF UNIQUE SERVERS VISITED

	Migration Frequency [#/day]						Migration Time [days]						Servers Visited [#]					
	Mean	Std. Dev.	Percentiles 5%	50%	95%	Fig.	Mean	Std. Dev.	Percentiles 5%	50%	95%	Fig.	Mean	Std. Dev.	Percentiles 5%	50%	95%	Fig.
All	0.02	0.07	0.00	0.00	0.10	8(a)	13.76	6.12	2.00	17.52	19.00	8(b)	1.36	0.80	1.00	1.00	3.00	8(c)
MigOnly	0.11	0.12	0.05	0.05	0.31	8(a)	7.18	2.51	2.51	8.51	9.51	8(b)	2.01	2.24	1.00	1.00	6.00	8(c)

TABLE II
THE TRANSITION PROBABILITIES (EXPRESSED AS PERCENTAGES) OF VM MIGRATIONS: MOVING FROM A PHYSICAL SERVER TO ANOTHER ONE

	HOST	**TO** A	B	C	D	E	F	G	H	I	J
FROM	A	0.00	91.69	4.98	1.95	0.72	0.32	0.15	0.10	0.07	0.02
	B	36.43	0.00	56.59	4.24	1.48	0.58	0.36	0.18	0.10	0.05
	C	20.94	31.38	0.00	42.11	3.47	1.19	0.42	0.28	0.13	0.08
	D	18.47	17.72	24.89	0.00	34.01	2.22	1.51	0.79	0.40	0.00
	E	15.75	13.65	15.49	22.66	0.00	27.82	2.10	1.22	1.05	0.26
	F	11.31	13.10	12.30	12.70	15.48	0.00	29.17	3.17	2.18	0.60
	G	11.30	13.36	7.53	12.67	8.22	18.15	0.00	26.03	2.05	0.68
	H	15.20	12.87	7.60	9.36	11.70	9.36	17.54	0.00	14.62	1.75
	I	19.59	16.49	4.12	13.40	10.31	8.25	11.34	10.31	0.00	6.19
	J	12.00	4.00	16.00	0.00	8.00	0.00	8.00	28.00	24.00	0.00

first occurrence within the observation period: the first host is labeled A, the second one B, and so on. Naturally, the shape of the empirical frequencies in Figure 8(c) directly affects the transition probabilities: i.e., all migrating servers have at least one A to B transition, while only few VMs migrate as far as to a J. One can also observe how the probability to migrate to the next or previous server in the sequence is much higher than skipping servers: i.e., the values next to the diagonal in Table II are significantly higher. The table demonstrates that even when VMs migrate, they tend to stay always within a restricted set of servers: i.e., one can expect ping-pong patterns between two servers to be the most frequent migrations.

To summarize, in this section we provided a description of contemporary migration processes in data centers. Consequently, the statistics presented here can be used to validate basic assumptions about workload migration patterns. Other uses are also possible, e.g., the frequency of VM migrations can be used to estimate how much additional load the underlying data center network infrastructure has to handle and the knowledge of existing migration patterns can be useful when it comes to improving VM placement strategies. Finally, Table I summarizes the main statistics for the plots presented in this section.

V. RESOURCE ALLOCATION AND VM MANAGEMENT

In this section, we study how resource allocation on boxes and VMs interacts with VM management policies. We are interested in two viewpoints: (1) long term averages on the entire duration of the trace, and (2) short term changes (that we also dab "instantaneous") within the smallest time granularity of the trace, i.e., within 15 minutes. Our purpose is pattern discovery aiming to better understand VM consolidation, by exploring the conditions that trigger migration from source to destination boxes, on/off patterns, and resource capacities. As in the previous analysis, we adopt two perspectives, one that focuses on the virtual machines and one that focuses on the physical boxes. We first categorize VMs/boxes by their levels of consolidation, on/off activity, and migration. Within each category, we compute the following statistics of interest: the median value, as well as the 25^{th} and the 75^{th} percentiles.

A. Consolidation

First, we focus on how the average CPU and memory capacities within each box are related to the VM consolidation level, i.e., the number of collocated VMs within a box. Results are summarized in Fig. 10. The figure illustrates 25% and 75% percentiles for number of CPUs and memory capacity in the form of whisker plots but also the corresponding medians in the form of bars. The figure clearly depicts that high consolidation levels are strongly and positively correlated to more hardware resources, both with respect to CPU counts and to memory availability. When comparing CPU and memory, one can see roughly 3X and 10X increments in number of CPU and memory, respectively, from the lowest to the highest consolidation level. Such a finding resonates to our previous results that the VM multiplexing level of memory is conservative and that memory has a linear relationship to the consolidation level on boxes.

B. On/Off Frequencies

1) VMs: Our first objective is to see whether there is any relationship among VM resources (i.e., vCPUs and vMEM) and the frequency that a VM is turned on/off. Results can be summarized as follows. There is no clear relationship among the size of a VM, the allocated resources, and the on/off frequencies. Data shows that big or small VMs have no difference in their on/off frequencies and that their resource allocation remains constant.

2) Boxes: The graphs in Figure 11 show the number of CPUs and memory allocated right after the VM is turned on again. Looking at the pCPU allocation (Figure 11(a)) there are distinctive trends for the number of allocated pCPUs and on

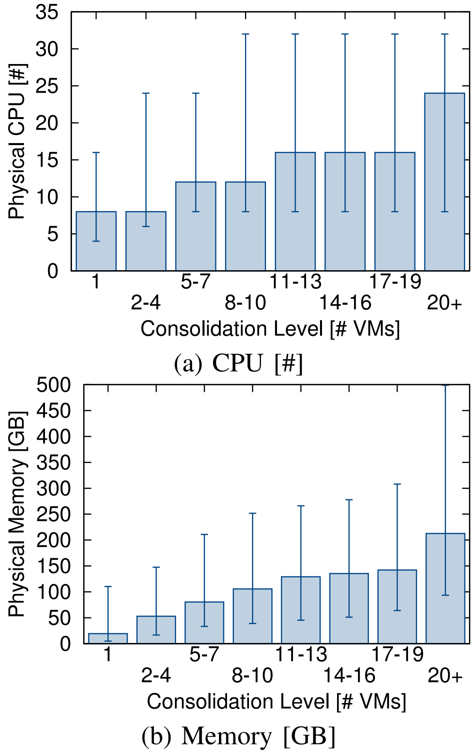


Fig. 10. The impact of consolidation level on physical resources (number of CPUs and memory).

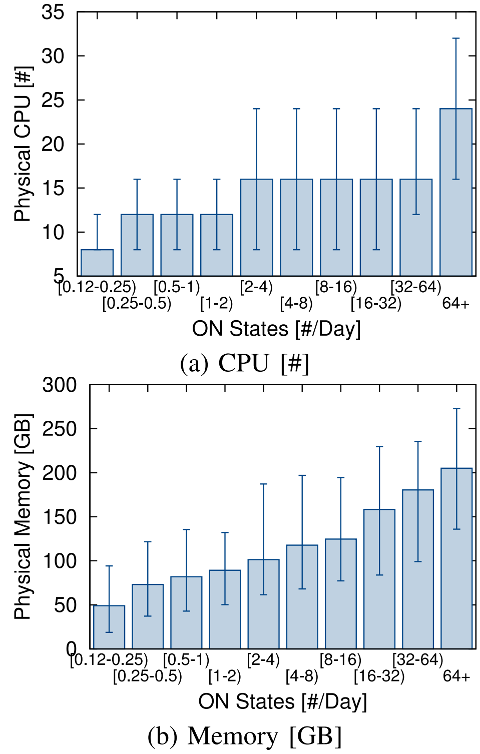


Fig. 11. Boxes' average resource allocation v.s. number of on/off.

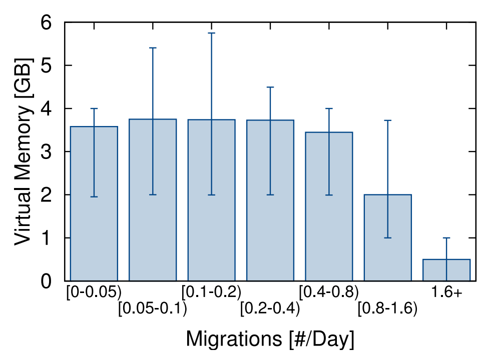


Fig. 12. Average memory allocation per VM as a function of migration frequencies.

the number of on/off times. Figure 11(b) focuses on physical memory (pMEM) allocation and shows a different pattern: there is a clear linear relationship on the allocated memory and the number of times the VM has been set on/off. In general, we observe that the number of times the VM is turned on/off relates to the number of its assigned pCPUs and it has a linear relationship with its allocated pMEM.

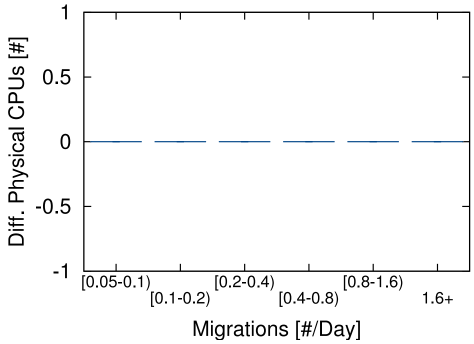
C. Migration

1) VMs: The main question here is whether smaller VMs tend be moved more frequently due to their lower migration overhead, due to the size of their active memory. Although the number of CPUs remains naturally the same, irrespective of the number of migrations, there is a clear negative trend that relates the number of migrations and allocated memory, see Figure 12. We also note that the resource allocation of VMs does not change during migration, i.e., the CPU number and memory size remain unchanged before and after migration. All in all, VMs with bigger vMEM allocation tend to be migrated less often.

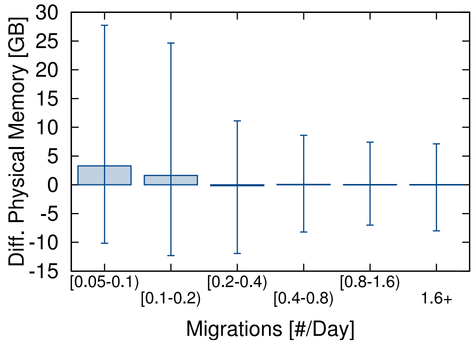
2) Boxes: One objective of our investigation is to discover whether there is any dependency between resource allocation and VM migration frequencies and if VMs are migrated across similar boxes, i.e., equipped with similar CPU/memory capacities, by checking their instantaneous differences in the 15-minute period right before and right after migration. Fig. 13 summarizes the hardware differences in boxes as a function of migration frequencies. For pCPUs, the differences are truly negligible, hovering at around zero. Note that the 25% and 75% whiskers are plotted but not even visible. For pMEM, although the median relative values are very close (with a maximum average difference of only 3 GB), the fact that the whiskers marking the percentiles are quite apart, indicates that memory can vary significantly. Yet, looking at medians, a difference of 3 GB is rather small considering the fact that the average memory allocation per box is around 60 GB. In sum, Figure 13 shows that in the majority of cases migrations occur across "similar" boxes.

VI. Resource Utilization and VM Management

In the previous section we focus on resource allocation per VM. Here, we do a similar analysis but we focus instead on physical resource utilizations, aiming to develop a better understanding of how VM management policies change data center usage given that we have no means of knowing the exact policies used for management. From our statistical analysis one can infer the general policy and explore whether there

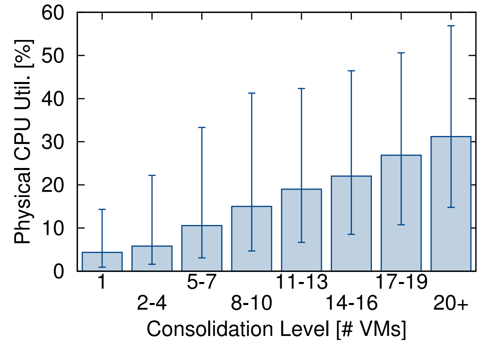


(a) CPU [#]

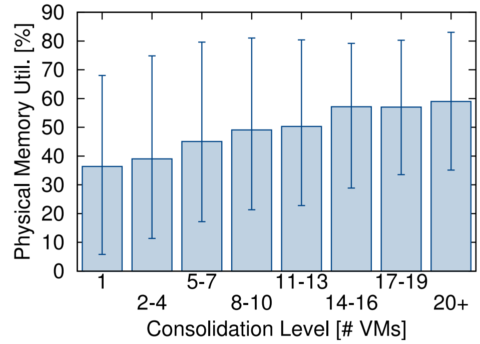


(b) Memory [GB]

Fig. 13. Instantaneous differences in boxes visited before and after migration (CPU and memory), as a function of migration frequencies.



(a) CPU [%]



(b) Memory [%]

Fig. 14. Average resource utilization on boxes vs. VM consolidation levels.

is room to improve data center usage. We focus on both average utilization values as well as instantaneous differences (i.e., within the next 15 minutes after an action occurs), aiming to discover the condition that triggers VMs to be turned on/off as well as migration.

A. Consolidation

We first focus on the relationship of median box utilization levels relatively to the VM consolidation on each box. One would expect that boxes with higher consolidation levels have higher resource utilization. The results in Figure 14 confirm the expectation that both pCPU and pMEM utilization increase nearly linearly as a function of the consolidation level.

Figure 14 should be viewed in conjunction with Figure 10 where VM consolidation levels are present together with the number of pCPUs and the size of pMEM used. Figure 10 allows to better understand the increments in CPU and memory utilization observed in Figure 14. Indeed, factoring in the availability of more CPU and memory resources, we see that indeed current consolidation strategies do take excellent advantage of the hardware availability.

B. On/Off

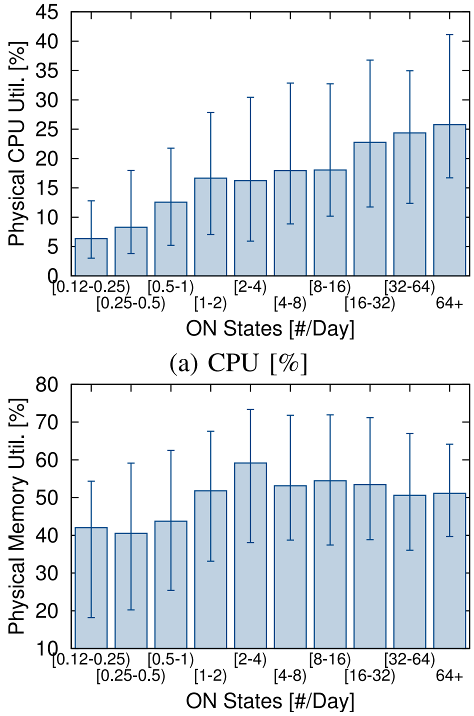
1) VMs: The question of interest here is which type of VMs are subject to frequent on/offs, i.e., is it the ones with higher or lower utilization. The results are not shown here in the interest of space, but can be summarized as follows. By inspecting the average CPU and memory utilization as a function of different on/off frequencies, we remark that there is no dependency between them. This leads to the conclusion that VMs experiencing frequent on/offs have no specific resource characteristics, i.e., neither resource utilization nor allocation (see also Section V-B1).

We also observe a similar relationship looking at the average instantaneous resource utilizations, i.e., observing the 15-minute window utilization statistics after an off event. Across the entire spectrum of VM on/off frequencies, the average differences in pMEM as well as pCPU utilizations are negligible, i.e., below 0.5%, before and after turning off a VM, which clearly implies that VMs are not turned off due to physical resource utilizations. We reach to a similar conclusion when considering long term average of resource utilization: VMs are not turned on/off due to resource utilization reasons.

2) Boxes: Our aim here is to understand whether VMs are turned on/off as a means to modulate resource utilization. We plot the average resource utilization and instantaneous difference of resource utilization with the number of VM on/off experienced by boxes in Figure 15. Figure 15(a) illustrates that VMs, that are not turned on/off frequently, tend to reside on boxes that are the least utilized. This is possibly an effect of capacity planning since important VMs (e.g., a Web server VM that needs to be continuously operating) needs to have excellent response times. pMEM utilization shown in Figure 15(b) seems to not be related as strongly to the on/off frequency of the residing VMs.

C. Migration

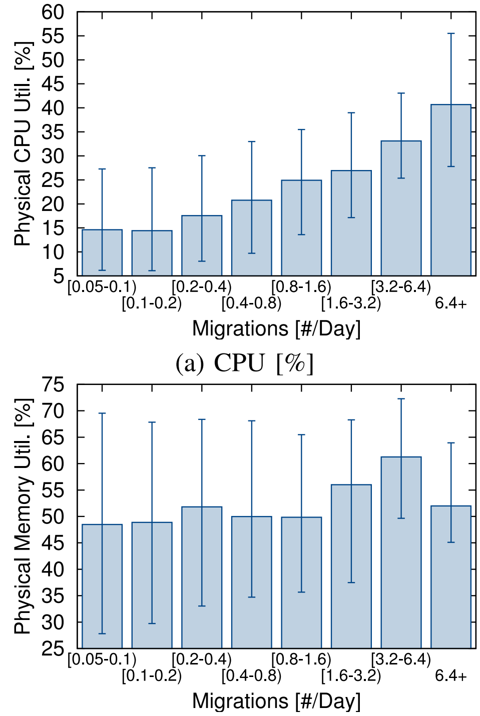
1) VMs: The focus here is to identify if VMs with higher resource utilization are subject to more frequent VM migration. As in the previous section, we focus on average resource



(a) CPU [%]

(b) Memory [%]

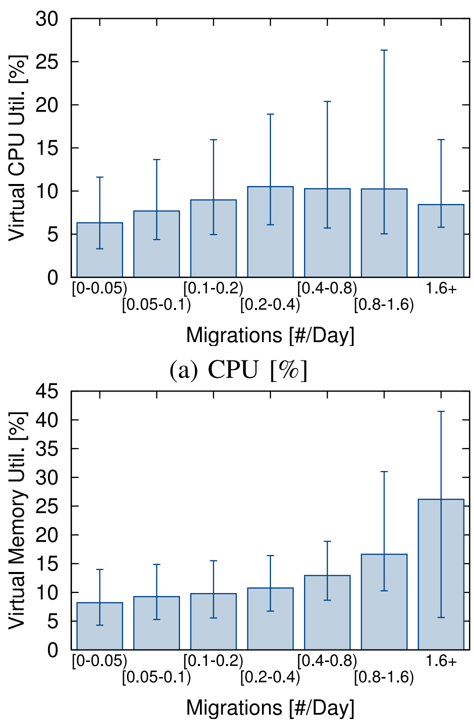
Fig. 15. Average resource utilization vs. on/off frequencies on boxes.



(a) CPU [%]

(b) Memory [%]

Fig. 17. Average resource utilization in boxes as a function of VM migrations.



(a) CPU [%]

(b) Memory [%]

Fig. 16. VMs' average resource utilization v.s. migration frequencies.

utilizations as well as instantaneous (i.e., within the upcoming 15 minutes) resource utilizations. Figure 16 depicts the vCPU and vMEM utilization values as a function of the VM migration frequency. The figure shows that CPU(memory) utilization roughly increases from 6%(8%) to 9%(25%), as a function of the number of migrations. While average vCPU utilization values remain overall low, the 75% percentiles show a different trend, i.e., there is a clear tendency for a good percentage of VM utilizations to be high and be associated with the number of migrations. Average vMEM utilization values are more strongly related with the number of migrations, as also are percentiles. The observed utilization trends are clearly more pronounced for vMEM rather than for vCPU.

We have also looked at the instantaneous differences in resource utilization before and after migration, results are not plotted here in the interest of space but can be summarized as follows. VM resource utilization levels remain unchanged after migration.

2) Boxes: Here, we focus on resource utilization of the hardware boxes before/after migration to answer the following questions: (1) do VMs migrate across boxes with similar utilization levels, (2) what happens to the resource utilization level of the source boxes, and (3) what happens to the resource utilization level of the destination boxes. We first focus on the average box resource utilizations changes as a function of the number of migrations, see Fig. 17. The figure illustrates a clear trend in increasing pCPU utilization with respect to VM migration frequencies: boxes that experience many migrations tend to be more utilized. The trends for pMEM utilization show instead that the average number of migrations per box is independent of its memory utilization. In sum, the figure corroborates that migration is more related to the box CPU utilizations rather than its memory utilization.

We next focus on the instantaneous resource utilization difference split by time of migration. For each VM we plot the

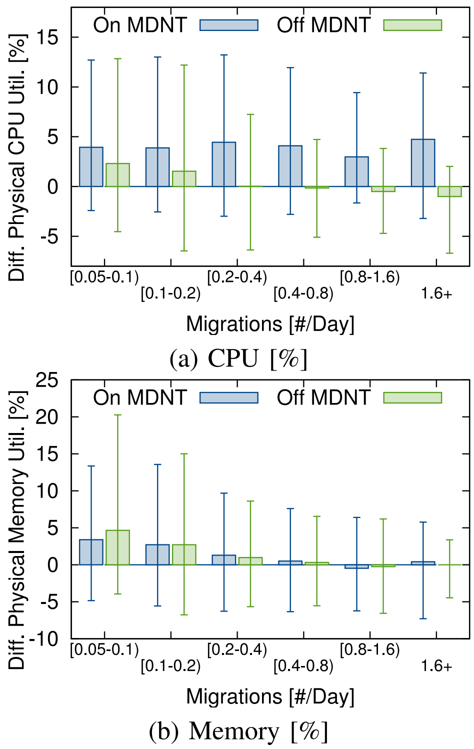


Fig. 18. Instantaneous resource utilization difference between source and destination boxes, split by time: around midnight (MDNT) and away from MDNT.

exact difference in resource utilization at the source and destination hosts, see Figure 18, looking to see whether most migrations occur toward more or less "busy" boxes. Since most migrations happen around midnight, as seen in Section IV-C, we distinguish migrations around midnight – 11 pm to 1 am – from all other migrations. Positive numbers indicate that migrations are toward less utilized boxes. Indeed, for both categories the box plots (see the width between the 25% and 75% percentiles) indicate that the overall tendency is toward migrations to less busy boxes. Nonetheless, for VMs that either migrate a lot or migrate a lot but not on midnight, the average tends to be zero. Comparing the midnight migrations versus all others, we see that utilization differences are significantly higher than those that occur during the day, hinting that these, although pre-scheduled, aim to better load balancing. Better pCPU (rather than pMEM) load balancing seems to drive these migrations.

The next interesting question related to migration is what happens to resource utilization levels of source and destination boxes, before and after VMs migrate in/out of them. In Figure 19, we summarize the instantaneous pCPU/pMEM utilization differences at the source and destination boxes, right after a VM migration. Across both source and destination boxes, we see that median utilization differences grow with the VM migration frequency, especially for pCPU. Another observation that is worth mentioning is that the values of utilization differences in the source boxes are lower than destination boxes, for both CPU and memory. Overall, there is a clear tendency to "equalize" resource usage across boxes as a function on migration activity.

VII. Summary of VM Management

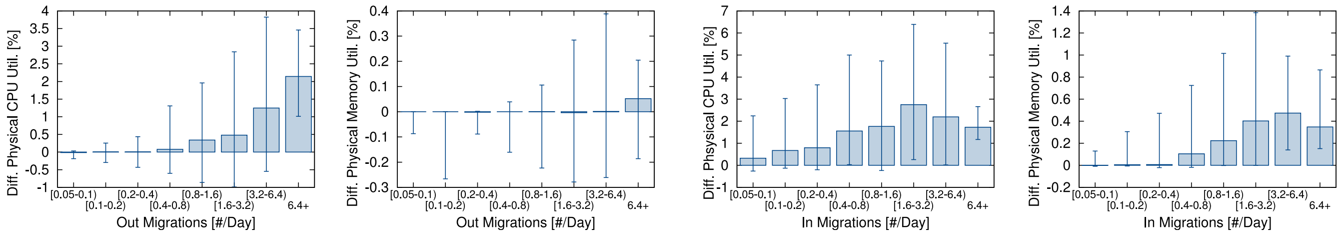
The scope of our study here is in a way restricted by the deluge of actual data, both a blessing and a curse. In this section, we attempt to give an overview that summarizes most aspects of VM management and resource usage. To this end, we use the Pearson correlation coefficient, a simple mathematical structure that projects the relationship of two data sets into a single number that ranges from -1 to 1. Correlation values greater than 0 imply that high/low values in one set correspond to high/low values in the second set, respectively. Negative values indicate that low/high values in one set correspond to high/low values in the second set, respectively. Values close to zero indicate independence among the two sets. Here, we consider correlations among consolidation levels, on/off frequencies, migration frequencies, CPU/memory allocations and CPU/memory utilization. As some of the metrics are varying over the observation periods, such as consolidation levels, resource allocation and utilizations, we use the average values across time for each VM and box. Results are summarized in Table III and IV that give the per VM and the per box view, respectively.

The correlation coefficient values are rather low in Table III, i.e., all values are less than 0.09, showing with a single number what we have seen with the box-plots in the previous section: VM activity is independent of VM resource requirements.

Table IV focuses on boxes and shows a more interesting perspective from the point of view of resource management and load balancing. Here, the correlation coefficients are significantly higher. Looking at the first row of Table IV, it is clear that there is a very strong positive correlation between the number of VMs hosted on a box and every other reported measure, from its hardware capacities to their utilizations and VM activity. Boxes with high resource capacities tend to host a high number of VMs that are very active. The number of migrations is clearly strongly correlated with the box CPU utilization, with migration been driven by resource management and load balancing. Section VI-C also provides the same perspective: box resource utilization is shown to be clearly related to migration activity rather than on/off frequencies. Finally, the last four rows of Table IV clearly show that hardware capacities and utilizations are closely related to one another: the number of CPUs strongly relate to boxes' memory, larger boxes are less utilized than smaller ones, and CPU and memory are naturally provisioned together.

VIII. Related Work

In the past decade there has been a host of research focusing on the development of robust virtualization technologies and management policies. Virtualization-related works can be roughly classified as those that focus on virtual resource provisioning, those that focus on how to best consolidate applications with different workload characteristics, those that put an emphasis on how to dynamically allocate resource capacity to better meet changing user demands, and those that relate to efficient ways to apply VM migration. In this section, we give an overview of some representative works; an exhaustive survey is not possible due to space restrictions.



(a) Source CPU [%] (b) Source Memory [%] (c) Destination CPU [%] (d) Destination Memory [%]

Fig. 19. Source and Destination boxes: instantaneous resource utilization before and after VM migrations.

TABLE III
VMs' Correlation Coefficient Matrix: Based on the Average Values of Migration, On/Off, Resource Allocation and Utilization

Migrations [#]	1.00					
On/Offs [#]	0.04	1.00				
CPU [%]	0.02	0.01	1.00			
MEM [%]	0.00	0.00	0.02	1.00		
CPUs [#]	0.01	0.01	0.09	0.02	1.00	
Memory [GB]	0.01	0.00	0.00	0.00	0.02	1.00
	Migrations [#]	On/Offs [#]	CPU [%]	MEM [%]	CPUs [#]	Memory [GB]

TABLE IV
BOXs' Correlation Coefficient Matrix: Based on the Average Values of Migration, On/Off, Resource Allocation and Utilization

VMs [#]	1.00						
On/Offs [#]	0.38	1.00					
Migrations [#]	0.22	0.08	1.00				
CPU [%]	0.45	0.18	0.26	1.00			
MEM [%]	0.29	0.04	0.13	0.42	1.00		
CPUs [#]	0.44	0.21	0.00	0.12	0.07	1.00	
Memory [GB]	0.52	0.21	0.08	0.09	0.02	0.68	1.00
	VMs [#]	On/Offs [#]	Migrations [#]	CPU [%]	MEM [%]	CPUs [#]	Memory [GB]

Understanding the relationship of physical to virtual resources is motivated by the need to accurately estimate resource demand and allocate virtual resources to VMs, which share or compete for the limited physical resources. Lu *et al.* [7] propose a methodology that uses a directed factor graph to model the multivariate dependence relationships among different resources (CPU, memory, disk, network) across virtual and physical layers. Wood *et al.* [8] use benchmarks to understand how the CPU utilization of an application is altered when moved from native to virtualized hardware, and develop regression-based models that can predict the CPU demand. Similar work is done in [9].

Consolidating different VMs on the same physical servers and their performance interference has been the focus of many works. Satisfying collectively the fluctuating capacity requirements of multiple VMs by best matching "peaks and valleys" is addressed in [10] and [11]. The use of a control-theory approach for sharing resources among competing VMs whose SLOs or resource requirements fluctuate over time is reported in [12]. A queuing-network based methodology uses workload characteristics for predicting the performance of VM consolidation [13] by classifying applications as CPU or IO intensive. Wood *et al.* [14] propose a methodology for VM co-location based on application memory access patterns. The communication pattern of applications can be also used to guide VM consolidation [15]. Numerous works also address the VM consolidation problem from the perspective of optimizing power usage [16], [17].

The ability to migrate a VM to different hardware when performance conditions deem it necessary provides additional flexibility in resource allocation and consolidation in a data center setting. Clark *et al.* [1] present a tool that can effectively achieve live migration of executing applications and illustrates the performance slowdown due to migration. A cost-sensitive approach that considers the adaptation cost of migration in multi-tier applications is given in [2]. A model that predicts the duration of live migration and its impact on application performance in a cloud setting is presented in [3]. Yet, the conventional wisdom is that the cost of live migration is high, therefore techniques that avoid such live migration are preferable [18]. Gmach *et al.* [19] present a tool for consolidating workloads that evaluates whether a fixed-capacity VM resource configuration is preferable to finer resource sharing, and discuss the merits of re-consolidating workloads after a fixed time period or using an automated consolidation process.

The combination of VM consolidation and migration yields various dynamic reconfiguration strategies. Proactive resource provisioning based on time series analysis and on forecasting combined with feedback control is proposed in [20]. Multiple input-multiple output [21] and Kalman filter-based [22] feedback controllers aware of multi-tier applications are used for CPU resource provisioning. Genetic algorithms can optimize VM consolidation [23], with a special emphasis on the possibility of dynamic VM resource capacity adjustments. Distributed artificial neural networks facilitate resource allocation [24], optimizing based on a custom utility function evaluated in cooperation among VMs. The multi-dimensional nature of resource allocation naturally leads to algorithms based on simulated annealing [25] and distributed plant growth simulation [26]. A dynamic optimization framework for OpenStack [27] is developed [28], providing a testbed for a diversity of configurable algorithms for VM consolidation and resource allocation.

The intent of this paper is to present a detailed workload study from corporate data centers and try to shed light on the problems of configuring VMs' virtual resources, VM liveness and migration patterns. To the best of our knowledge, this is the first workload characterization study on corporate data centers that shows the current practice in VM configuration, consolidation, liveness, and migration. The extent of the study is what sets us apart from other related work: we do not report the behavior of a small, experimental system in a laboratory setting but instead we report on the actual usage patterns in the corporate world.

IX. Conclusion

We present a detailed characterization study of virtualization technologies in today's data centers, based on vastly diversified systems. We focus on how physical resources, i.e., processors and memory, are shared by VMs through virtual resources and give a summary of statistics describing physical hardware and VM configurations. Furthermore, we show the common characteristics of VM lifetimes and their migration patterns, including migration frequency and transition probabilities across different physical servers. The presented statistics provide an overview of how virtualization technologies are used in practice. Our findings illustrate that conservative approaches are the prevailing ones: i.e., most of VMs never migrate, and those that migrate do not do so often. In addition, VMs tend to migrate with specific spatial patterns, i.e., the transition probabilities from certain physical servers to certain others reflect strong affinities among physical servers. Distinct patterns are also found at times when the majority of VMs are turned on and when they mostly migrate (at midnight), pointing to the prevalence of routine applications (perhaps maintenance ones). We also reported on the durations of VM on and off periods and saw that a significant percentage of VMs are continuously on in contrast to those that are switched on and off.

In this paper, we provided a generic view of how virtualization technologies are utilized in contemporary data centers in the private cloud. In the future, we intend to continue this work and conduct a more detailed study that can shed more light on differences and similarities across data centers used by specific industries.

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