

On the Energy-Proportionality of Data Center Networks

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Abstract—Data centers provision industry and end users with the necessary computing and communication resources to access the vast majority of services online and on a pay-as-you-go basis. In this paper, we study the problem of energy proportionality in data center networks (DCNs). Devices are energy proportional when any increase of the load corresponds to a proportional increase of energy consumption. In data centers, energy consumption is concern as it considerably impacts on the operational expenses (OPEX) of the operators. In our analysis, we investigate the impact of three different allocation policies on the energy proportionality of computing and networking equipment for different DCNs, including 2-Tier, 3-Tier and Jupiter topologies. For evaluation, the size of the DCNs varies to accommodate up to several thousands of computing servers. Validation of the analysis is conducted through simulations. We propose new metrics with the objective to characterize in a holistic manner the energy proportionality in data centers. The experiments unveil that, when consolidation policies are in place and regardless of the type of architecture, the size of the DCN plays a key role, i.e., larger DCNs containing thousands of servers are more energy proportional than small DCNs.

Index Terms—Energy-efficiency, energy-proportionality, data center networking.

1 INTRODUCTION

CLOUD computing has become fundamental for IT operations worldwide. Industry and end users can now access the vast majority of services online without having to invest into acquiring a proper IT infrastructure. Data centers provision industry and end users with the necessary IT infrastructure, including computing and networking resources, which are consumed on a pay-as-you-go basis.

Data Center Networks (DCNs) are the topologies interconnecting computing and communication nodes within the data centers and provide connectivity among the servers and towards the end users. DCNs have an important role on the performance perceived at application level, such as requested throughput and response latency.

To provision the services, data centers consume a tremendous amount of energy that is contributing to increase concerns for the environment [1]. Computing devices are more energy-hungry than network devices, but since servers are becoming more energy efficient, the network contribution cannot be ignored. According to Abts et al. [2], if a data center is used at 15% load and servers are fully energy proportional, the network contribution is close to the 50% of the overall power consumption.

Another important trend in data center industry regards the size of data centers. Smaller data centers are consolidating

in bigger ones, composed by several thousands of computing servers, the so called *mega data centers*. Mega data centers, leveraging on the economy of scale, allow operators to offer more competitive services to the end users reducing some of the operational costs of the facility. By 2018 the number of mega data centers is expected to be 70% of the total amount of worldwide facilities [3]. Typically, the operators do not reveal the number of servers contained in each facility. However, according to data center analysts, large data centers can host up to 50,000-100,000 servers [4]. The number of servers in any facility can be estimated exploiting the data center design requirements [5]. For a cloud data centers, 12 kW is the typical average power per cabinet design target. The QTS data center located in Chicago is large 133,000 square feet and provides 24 MW of power capacity [6]. Considering that each cabinet can host up to 40 servers and consumes 12 kW, then the data center is estimated to contain up to 80,000 servers. The Ashburn VA2 data center, located in Northern Virginia [7], measures 140,000 square feet and consumes 14 MW of high density critical IT power. Using the same reasoning, this facility can host about 50,000 servers.

The growing demand for traffic, the explosion of cloud services and the advent of mega data centers push high the demand for performance and require increasingly efficient, performing and flexible networks. New DCNs are appearing on the scene, claiming high scalability and huge bandwidth [8], [9]. The most promising solutions exploit a large number of low-radix communications nodes, combined in recursive hierarchical tree [10], [11]. These DCNs are being adopted in mega data centers to connect hundred of thousand of server. But the explosion of the number of servers and switches in data centers is ramping up the energy consumption, bringing out the need for new solutions for energy efficiency. At best of our knowledge, little effort has

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been spent to investigate the implication of this growing sizes on the consumption of the data centers.

1.1 Our Contribution

In our work¹ we provide an asymptotic analysis of how the power consumption grows with the size of data centers. Our results can help to understand the impact of the adoption of these trends on the OPERational EXpenditure (OPEX) of the operators. We compare the energy performance of different DCNs, varying the layout of the adopted topology and the size. We focus on the energy proportionality, a concept that was first introduced by Barroso et al. as a fundamental property to assess energy efficiency [13]. A device, or a system, is defined *energy proportional* if consumes energy proportionally to the amount of work performed. An energy proportional device is efficient at various utilization levels: in idle mode, it does not consume power at all and at each increase of the workload, the power consumption increases gradually.² Energy proportionality can be measured locally, considering the consumption of a single device (server or switch), or at global level observing the cumulative consumption of all the components of the data center. We will focus on the latter contribution, since for data center operators, assessing global energy proportionality is of paramount importance to predict the variation of energy consumption with increasing workloads, and thus to evaluate the revenues.

To study the energy proportionality problem, we define three different allocation policies that characterize the assignment of Virtual Machines (VMs) to the computing servers. Specifically, we consider both *consolidating policies* that aim at concentrating the load in the minimum number of servers and *load balancing policies* that distribute the load across all the servers. The impact of the different allocation policies is studied for several DCNs, including 2-Tier, 3-Tier layouts and Jupiter, which is the reference DCN for Google [14]. Throughout simulations, we evaluate the energy efficiency in a holistic manner considering several performance metrics: the energy proportionality of both computing and communication equipment (Energy Proportionality Error), the energy cost spent to allocate incoming VMs at various utilization levels of the data center (Power Per Virtual Machine) and the efficiency of the network expressed in terms of energy consumption per bit of information delivered (Network Power Efficiency).

The main contributions of this work are as follows:

- An asymptotic analysis of data center power consumption for different size and typology of DCN with the objective to investigate the contribution of different allocation policies to the energy proportionality.
- New metrics to assess energy proportionality of computing and communication equipment and network efficiency.
- A simulator of data center where communications are modeled at flow level. The simulator is designed to be configured with different DCNs and allocation policies, and permits to assess power consumption at fine-grained level, by calculating the contribution to the

1. A preliminary version of our work was presented in [12].

2. Similarly to [1], in the rest of the paper we use power and energy interchangeably as data centers are typically required to be always on.

consumption on network and computing resources due to each single VM allocation.

1.2 Main Findings

Our main findings are the following. The size of the data center impacts on the global energy consumption more than the considered layout. Thus considering two DCNs with similar size and performance (latency, bisection bandwidth, etc.), the way in which servers and switches are interconnected does not impact consumption. Moreover, when consolidation policies are employed, the larger is the size of a data center, the more the energy proportionality becomes independent of the layout of the DCN. At any operational load, larger data centers containing thousands of servers are more efficient than data centers with few hundreds of servers. This consideration is true for any DCN, but on the condition that the load on the servers is consolidated and not distributed. As the demands for cloud services are continuing increasing and force the building of mega data centers, the adoption of consolidation policies will boost efficient use of energy.

The paper is organized as follows. Section 2 illustrates the DCNs used for the analysis and presents the methodology adopted to profile energy proportionality in data centers, including the new proposed performance metrics. Section 3 describes the computing and communication model the simulator implements, including the VM arrival process and the resource allocation policies. Section 4 illustrates performance evaluation and Section 5 discusses and elaborates on the results obtained. Section 6 reviews related works and Section 7 draws conclusions outlining future research directions.

2 PROFILING ENERGY PROPORTIONALITY OF DATA CENTERS

We investigate the data center energy efficiency in function to the offered load and the size of the data center. We consider the contributions of both servers and switches. A DCN not only determines the topology of the network and the number of its components, but also defines the number of servers that can be supported. Therefore, as the size of a data center grows the power spent to operate the IT equipment increases. However, the increase of power consumption due to a large number of available resources is different for each DCN. As mega data centers support several thousands of servers and are designed to be scalable, the choice of a proper DCN that satisfies energy proportionality criteria can lead to significant energy savings and reduction of facility management costs.

2.1 Analysis of Data Center Networks

DCNs are networking infrastructures providing interconnection among the computing servers and between the computing servers and the Internet. Each DCN is arranged into a specific layout defining the interconnection properties of the network, such as the bisection bandwidth. DCNs are typically described as graphs where nodes represent servers and switches, and edges represents the communication links.

Two kind of switches can be found in a data center: *Top-of-Rack (ToR)* and *End-of-Row (EoR)* switches [15]. ToR switches

are small, low power Ethernet switches with a fixed number of ports. They are typically used to connect servers to the backbone of the data center. The name ToR derives from the fact that these switches are typically placed at the top of the rack and connect a group of servers. EoR switches, are large, modular switches composed by a variety of line cards, with different layer-2 interfaces and different combinations of switching fabrics and network processors. These switches have many more ports than ToRs. Since their dimension vary depending on the number of line cards used, typically they fill an entire rack. These kinds of switches can be identified with different terminology when placed inside the data center. For example in a 3-tier data center the switches connecting servers to other switches can be called *ToR*, *edge*, *leaf* or *access* switches. In the intermediate layer switches can be called *spine*, *aggregation* or *distribution*. In the majority of cases at the upper layer switches are indicate as *core*. In the rest of the paper we will refer to these switches respectively as ToR, aggregation and core switches.

The interconnection links between computing servers and ToR are typically 1 Gbps while aggregation and core switches have 40 Gbps Ethernet ports, which can be split in four 10 Gbps ports with the use of breakout cables. The demand for these high bandwidth switches is growing fueled by cloud application and by the decrease in the price of 10-Gbps network interfaces of servers [16]. Since DCNs networks are typically not used to their full capacity, operators choose to unbalance the input/output ratio at ToR level, to lower the design costs of the data center. This technique is called oversubscription and is defined as the ratio of the worst-case achievable aggregate bandwidth among the end hosts to the total bisection bandwidth of a particular communication topology [11]. For a n -ports switch and a server oversubscription of factor k , $n/(k+1)$ ports of a ToR are connected to the core switches and the remaining $nk/(k+1)$ ports to the servers (as realistic example, $k=3$ according to [14]). This implies that n/k core switches are present and connected to n ToR switches.

For the purpose of this paper, the analysis focuses on intra data center traffic of Clos-based DCNs [17]. Clos networks permit to build large-scale communication networks using few switches, with the same number of ports on all stages. Conversely, conventional DCNs [18] are built with fewer, more expensive and energy-hungry switches with a higher number of ports at each stage of the interconnection layout. Intra data center traffic, also known as east-west traffic, is the primary component in data centers as opposite to inter data center (north-south) traffic that corresponds to information exchange towards the wide Internet. Moreover, the vast majority of real-life workloads produce traffic that remains inside the data center. Since we consider that the two kinds of traffic generate the same effects on power consumption of the data center, for the sake of simplicity it has been decided to focus on intra data center traffic only. See Section 3.4 for further details on our communication model.

Fig. 1 illustrates the DCNs considered for the analysis, including 2-Tier and 3-Tier layouts [11] and Jupiter [14], which is the DCN adopted by Google in its data centers. The following paragraphs discuss and present the main properties of each architecture.

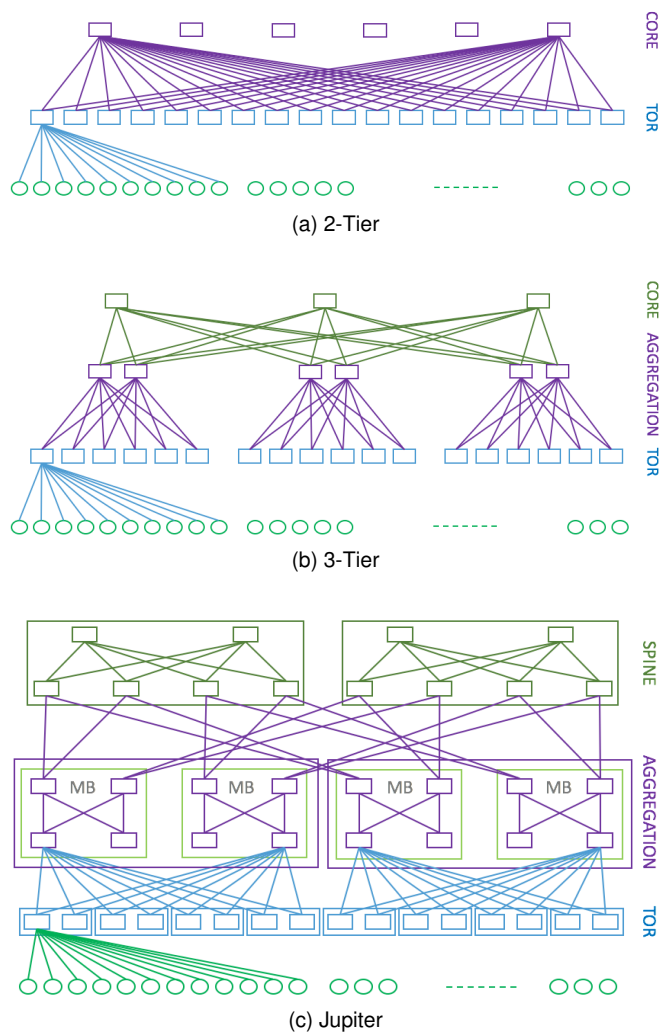


Fig. 1. Data center architectures used for the analysis

2-Tier: Fig. 1a illustrates a 2-tier DCN, which is based on a classical 3-stage Clos switching network and is commonly implemented in small data centers. Since the switches at the two levels are fully connected, its scalability is affected by the number of ports in the switches, which determine the number of core switches. As a consequence, large networks can be designed only with switches with high number of ports, which is not always possible. Let k be the oversubscription factor. Then, the 2-Tier design can support a maximum of $n^2k/(k+1)$ computing servers.

3-Tier: Currently, the vast majority of data centers implements a 3-Tier architecture, which is based on a classical 5-stage Clos network (see Fig. 1b). This DCN consists of three levels of switches, ToR, aggregation and core. Having n -port switches for all levels and k as oversubscription factor, a 3-tier architecture supports a maximum number of $n^3k/(2(k+1))$ servers interconnected with $n^2/2$ ToR switches, $n^2/(k+1)$ aggregation switches and $n^2/(2(k+1))$ core switches. This is one of the most adopted reference layout, since it supports a large number of servers.

Jupiter: To further extend the scalability of 3-Tier designs, Google proposed the Jupiter architecture [14], which is based on a 7-stage Clos network. Fig. 1c shows a simplified layout

of Jupiter, which exploits heterogeneous building blocks and is constructed in a recursive manner. The smallest unit is composed by a 16-port switch with 40 Gbps link rate, used for building the blocks of each layer and implemented with commodity switch chipsets. Each ToR are composed by 4 unit switches and is connected to 64 other devices. Aggregation blocks are splitted in sub-groups (called *Middle Blocks (MB)*), also composed by ToR switches placed on two levels. The upper layer is composed by 256 Spine blocks connected to 64 Aggregation blocks. As a result, Jupiter achieves high modularity, which permits to interconnect around 400,000 servers using 10 Gbps interconnection links for a bisection bandwidth of 1.3 Pbps, coherently with a value of 3 of oversubscription ratio.

2.2 Comparison Methodology

Comparing different types of the DCNs is challenging as several non-independent criteria can be employed as a base reference, like equal number of nodes (servers, or switches plus servers), equal bisection bandwidth, equal cost of the devices or equal power consumption. Being the criteria non-independent, fixing one has consequences on the others. For example, comparing DCNs with equal bisection bandwidth implies having by design a different number of nodes and consequently a different energy consumption. In this paper, we compare DCNs by fixing the number of computing servers.

The objective of the comparison is to assess the power consumption in function of the load. The consumption of the data center primarily depends on the power profile of the nodes, servers and switches and on the actual load on each node. The latter is driven by the adopted allocation policy.

Consider for example a simple scenario of a 2-Tier layout with 2 core switches, 4 ToRs, 2 servers for each ToR and a fixed power consumption for all devices, independently from their load. Suppose now that one VM is already allocated and a second one needs to be deployed. The two VMs need to communicate one with each other as a requirement. To accommodate the incoming VM into a server, there exist different allocation policies:

- 1) *intra-server* allocation, according to which the new VM is deployed in the same server of the first VM. This policy consolidates the computing and communication loads to minimize the number of devices in use;
- 2) *intra-rack* allocation, according to which the new VM is deployed in the same rack of the already allocated VM, but in a different server. This policy minimizes the impact on the network as the interconnection between the two servers is guaranteed by one ToR switch. Moreover, the policy balance the computing load among the racks.
- 3) *inter-rack* allocation, according to which the new VM is allocated in a different rack of the already allocated VM. This policy aims at balancing both computing and communication loads.

The three aforementioned policies impact on the utilization load of computing and communication devices and in turns on the overall power consumption of the data center. Performing an integrated analysis of *computing* and *communication* resources is therefore essential as lowering

the loads of one of the two components influence the loads of the other with a different global consumption of the data center. For this reason, we adopt an integrated methodology to assess the power consumption of the data center considering at the same time the consumption of the two kinds of resources. This is an important point of novelty with respect to previous works, which have been focusing on just one component at a time. In our work, the comparison is performed analyzing either the global consumption of the data center as well as the distinct contribution of the two components. The analysis of the separated contribution permits to understand how the allocation impacts on the consumption of the two components.

2.3 Performance Metrics

A number of metrics is currently used by industry and academia to assess efficiency of data centers. The most well known metrics are the Power Usage Effectiveness (PUE) [19] and the Performance per Watt (PPW) [20]. The PUE is computed as the ratio between the total energy consumed by the facility and the energy consumed by the IT equipment. Unfortunately, the insights given by the PUE strongly depends on a number of external factors and consequently this metric is not precise enough for the purpose of this paper. For example, the values of the PUE are affected by the season and weather conditions as these elements impacts significantly on the usage of the cooling system. Indeed, when the cooling system is used extensively, the fraction of overall power attributed to the IT equipment with respect to the overall power consumption reduces. As a result, the PUE assumes higher values and the data center appears to be less efficient. In addition to this issue, the energy consumed by the IT equipment is usually determined not accounting for a number of components that indirectly contribute to computing or communications purposes like fans and power suppliers. Performance metrics such as PPW, although applicable for the scope of this paper, take into account the performance of the hardware expressed in Millions of Instructions Per Second (MIPS) or Floating Point Operations Per Second (FLOPS). As a consequence, they depend on the efficiency of the adopted hardware, whereas in our paper, to assess the asymptotic behavior of different DCNs for different allocation policies, we assume that the smallest unit of computing and communication load corresponds to the one generated by a single VM.

In this work, we evaluate the *total power consumption* obtained by summing the contribution of the servers and of the network devices, and the *network power consumption*, obtained by considering only the contribution of the network devices. To fairly compare the performance of different DCNs, we rely on the average *Power-per-VM* (PPVM), defined as the ratio between the total power consumption and the effective load in term of VMs.

$$\text{PPVM} = \frac{\text{Total power consumption of the DCN}}{\text{Number of allocated VMs}}. \quad (1)$$

The PPVM metric is expressed in Watts and ensures a fair comparison among different DCNs as its definition is totally independent of the actual size of the data center. Moreover, the PPVM is useful for the data center operators to assess the operational costs of allocating each VM. In simplistic

terms, in current cloud business models, the revenues for the operators are related to the number of VMs running successfully.

In the literature, the energy proportional behavior of the devices has received considerable attention and a number of metrics such as the Energy Proportionality Coefficient (EPC) [21] have been proposed. More details on this are provided in Section 6. By construction, the EPC metric is not applicable to discontinuous power consumption profiles like step functions, which are typical in communication devices. To overcome this issue, we define a new metric, denoted as Energy Proportionality Error (EPE). The EPE index evaluates the deviation of a power consumption profile from the ideal curve as the sum of the absolute values of the difference of the areas in each step of the load. Specifically, the EPE index is defined as follows:

$$EPE = \int_0^1 |f(x) - x| dx, \quad (2)$$

where $f(x)$ is the normalized power consumption as function of the normalized offered load x of the data center. The subtracted function x corresponds to an ideal energy proportional curve like the FEP curve shown in Fig. 2. By construction, $EPE \in [0, 0.5]$. EPE is null whenever $f(x)$ is ideal energy proportional (i.e. equal to x), whereas EPE is 0.5 when $f(x) = 1$ for any x , i.e. completely constant.

For an in-depth analysis of the effect of communications on the overall power consumption, it is important to analyze the amount of power spent to transmit data. The *Network Power Efficiency* (NPE) index is defined as the ratio between the network power contribution and the effective network load generated by the VMs. The NPE index is expressed in W/Gbps and is formally defined as follows:

$$NPE = \frac{\text{Total network power}}{\text{Effective network traffic}}. \quad (3)$$

The effective network traffic is determined by monitoring the traffic on ToR switches and excluding signaling traffic necessary to manage and operate the network like routing. Thus, EPE does not consider the traffic exchanged between VMs located in the same server. Note that monitoring the intra-server traffic among VMs is possible through cloud managers like Neutron, which has the ability of accounting for traffic generated in virtualized environments at fine-grained level, but such information does not affect the energy proportionality of the DCN.

3 COMPUTING AND COMMUNICATION MODEL

We developed an ah-hoc event-driven simulator in C++ that models the whole data center, in terms of servers, interconnection network and VMs arrival and VMs allocation. The communication between servers is simulated at flow level, thus by allocating the requested bandwidth on the path connecting the source and destination VMs present in the servers. We argue that the simulation of the traffic at flow level is the only viable approach to investigate large data center networks, without losing accuracy in assessing power performance with respect to packet-level simulators, whose scalability is instead very limited. Additional details on the implemented simulation model is reported in [12].

More in details, the normalized load on server s is characterized by three values: $\rho_s^{CPU} \in [0, 1]$ for the CPU, $\rho_s^{RAM} \in [0, 1]$ for the internal volatile memory (e.g., RAM) and $\rho_s^{HD} \in [0, 1]$ for the non-volatile memory (e.g., hard-disk storage). All these values are normalized to the maximum capability available at the server. We assume heterogeneous resources across all the servers, thus we can directly sum all the normalized load to get the *overall average data center load*, defined as follows:

$$\rho_{tot} = \max \frac{1}{S} \left\{ \sum_{s=1}^S \rho_s^{CPU}, \sum_{s=1}^S \rho_s^{RAM}, \sum_{s=1}^S \rho_s^{HD} \right\}, \quad (4)$$

i.e. the maximum average load across the three kinds of resources. Whenever a VM is generated, it is associated with a random triple describing the CPU, RAM and storage requirement, and with a destination VM, chosen at random among the ones already allocated, with which the VM exchanges traffic.

3.1 Resource Allocation Policies

To allocate a sequence of incoming VMs, we consider the following three on-line VM allocation schemes:

- **Simple Server Consolidation (SSC)** scans the servers according to a given order and chooses the first one that can host the new VM. Thus, SSC is representative of a consolidation policy oblivious of the network state.
- **Random Server Selection (RSS)** chooses at random one server to allocate the new VM. Thus RSS is representative of a distribution policy that tries to load evenly the servers.
- **Min-Network Power (MNP)** chooses the server with minimum *network* power cost for the VM to communicate with its destination VMs that have been already allocated. Due to the power cost to communicate among servers, MNP is also a consolidation policy, but now network aware.

The pseudocode in Algorithm 1 shows the details the operational workflow of the three policies. For the sake of clarity and simplicity, the code is different from the one implemented in our simulations, even if they are functionally equivalent. Indeed, our implementation has been designed to minimize the computational complexity and thus extending the scalability of the approach for large data centers.

Referring to the pseudocode, all the policies receive as input the new VM v to allocate (ln. 1), with the set of destination VMs to communicate with and the corresponding bandwidth requests. Based on those, the corresponding set of servers where the destination VMs have been previously allocated and the required bandwidth requests are evaluated (ln. 2-3).

Now, a sorted list of candidate servers is created (ln.4) according to one of the three possible allocation policies. In RSS the candidate server is chosen at random (ln. 17), in SSC the most loaded server is selected (ln. 20-22), whereas in MNP it is chosen to minimize the potential increment of power consumption due to the new VM, based on the power profile of all the switches along the routing path. Indeed, for each possible candidate server (loop in ln. 24-30), MNP computes the incremental power due to reserve the bandwidth along the path from the candidate server for VM

Algorithm 1 VM allocation policies

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1: procedure FIND-SERVER-FOR-VM( $v$ )
2:    $\Omega \leftarrow$  list of all the destination servers of VM  $v$ 
3:    $B \leftarrow$  list of all bandwidth requests of VM  $v$  for all the destination servers
   in  $\Omega$ 
4:    $\pi \leftarrow$  SORT-SERVER-RSS( ) or  $\pi \leftarrow$  SORT-SERVER-SSC( ) or  $\pi \leftarrow$  SORT-
   SERVER-MNP( $\Omega, B$ ) ▷ Specific order for each
   policy
5:   for  $i = 1 \dots S$  do ▷ Loop on all the possible candidate servers
6:      $s = \pi_i$  ▷ Pick next server
7:     if server  $s$  has enough local resources for VM then
8:       if server  $s$  has enough bandwidth towards all servers in  $\Omega$  then
9:         allocate VM on server  $s$ 
10:        reserve the bandwidth from  $s$  to all servers in  $\Omega$ 
11:        return  $s$  ▷ End of search: VM  $v$  is allocated in server  $s$ 
12:      end if
13:    end if
14:  end for
15:  return BLOCKING-EVENT ▷ VM cannot be allocated due to lack of
resources
16: end procedure

17: function SORT-SERVER-RSS( )
18:  return random permutation of  $S$  servers
19: end function

20: function SORT-SERVER-SSC( )
21:  return permutation of  $S$  servers in decreasing server power  $\delta_s$ 
22: end function

23: function SORT-SERVER-MNP( $\Omega, B$ )
24:  for  $s = 1 \rightarrow S$  do ▷ Search across all the servers
25:     $\delta_s \leftarrow 0$  ▷ Init incremental power to reach candidate server  $s$ 
26:    for any  $d \in \Omega$  do ▷ Consider all possible destinations for  $s$ 
27:       $\mathcal{P} \leftarrow$  path with minimum power cost from  $s$  to  $d$ 
28:       $\delta_s \leftarrow \delta_s +$  additional network power due to  $B_d$  traffic on  $\mathcal{P}$  path
29:    end for
30:  end for
31:  return permutation of  $S$  servers with increasing network power  $\delta_s$ 
32: end function

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to all the destination servers (ln. 26-29). Finally, the list of candidate servers is returned sorted in increasing network power.

For both policies, the main loop (ln. 5-14) considers each candidate server sequentially, and checks whether the server has enough local resources (ln. 7) and whether the network provides enough bandwidth (ln. 8) to satisfy the bandwidth requests from the VM to its destination VMs/servers. If both condition are met, the candidate server is selected, otherwise the next candidate is considered. In the case the search is not successful, the VM allocation is blocked (ln. 15) since either no enough resources are available in the servers or no enough bandwidth is available in the network to satisfy its communication demand.

When comparing the different approaches, RSS distribute the VMs across all the servers in the data center, thus distributing the traffic in the whole network. Instead, MNP and SSC consolidates the VMs in the available servers, minimizing the network communications and thus the network power consumption.

3.2 VM Generation Process

Typically, the data center load is defined as the cumulative amount of resources (CPU, storage, memory, communication bandwidth) requested by the VMs that are effectively allocated in the data center. We define the load based on most constrained resources for both communication and computing. For the communications, the switch load depends on the allocated bandwidth and, without loss of generality, for the computing the servers are loaded considering just the

CPU, to simplify the definition according to (4). In this way the single request of the VM consumes a fraction of the total capacity of the available resources.

For a simple, fair and repeatable comparison, we have defined a benchmark generation process of VMs with the following assumptions: VMs are generated sequentially, cannot migrate and never expires. The effect of migration in our findings will be later discussed in Sec. 5.1.

Each VM may be associated to a set of other preexisting VMs, denoted as *destination VMs*, that have been already allocated in the data center and with which the new VM must communicate. A bandwidth request is associated for each destination VM. Note that a newly allocated VM may become destination for other future VMs, and this enables the communication with multiple VMs at the same time; this makes our VM model quite general. Indeed, it captures different possible cases, being compatible with the scenario of isolated VMs (i.e. without any communication requirement) and also with the scenario of small or large clusters of VMs that communicates each other. This model can be applicable to different real scenarios with high intra-data center traffic such as indexing applications, distributed storage systems, MapReduce workloads. See Section 3.4 for further details.

Let the *offered load* (L_o) be the load given by the arrived VMs, normalized with respect to the data center resources. Note that, according to [22], the average offered load for operational data centers running several types of workloads, including online services, is around [0.2, 0.5]. Since the available resources in terms of computing and communication are finite, a request for a new VM (typically at high offered load) may not be accommodated: this is defined as “blocking event”. Thus, the *effective load* (L_e) is defined as the normalized load of the VMs that have been successfully allocated. We define the *blocking load* as the minimum load when the first blocking event occurs. Intuitively, the blocking load is the effective load capacity of the data center, i.e. its saturation point. To fairly compare different scenarios, the EPE index is always computed for load values lower than the blocking load. Allocations after this point are often unsuccessful and depend on the residual capacity of resources and size of the VM to be allocated. Thus, we avoided to show results above the blocking load.

The adopted simulation methodology with arrived VMs brings two major advantages. First, it is possible to test the allocation policies for different values of loads with just one simulation run. Multiple runs are only repeated to obtain confidence intervals for the desired results. Second, it is possible to keep feeding the data center until it completely saturates either in terms of computing or networking resources, which permits to assess the performance under a worst-case load scenario.

3.3 Power Consumption Profiles

In the scientific literature, a number of energy models for data centers is available [23]. In this work, we model both computing and communication equipment.

Fig. 2 illustrates the profiles modeling the power consumption of IT equipment. The power consumption profile of a real device is typically described by a generic function where at the loads $l = 0$ and $l = l_{\max}$ correspond P_{idle} and P_{peak} respectively. Fig. 2 denotes as REAL such a profile.

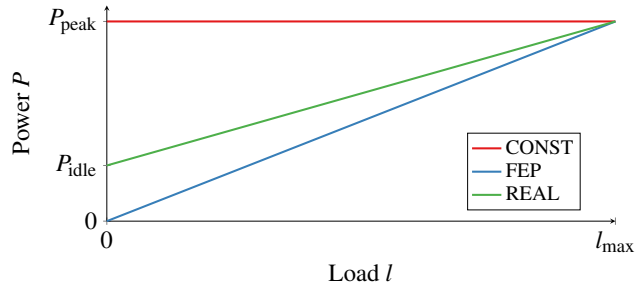


Fig. 2. Power consumption profiles for the IT equipment

The power profile of an ideal device does not consume any power under zero load and it increases linearly with the load, reaching P_{peak} under the maximum load l_{max} . We denote this profile as Full Energy-Proportional (FEP). Although being ideal and therefore not available in current devices, the FEP profile can be considered as a benchmark for comparing other profiles especially at low loads.

On the other side, the constant power consumption profile (CONST) models a device completely insensitive to the load, for which the power spent remains always constant to P_{peak} . This profile provides very bad performance, especially for low levels of load, and can be considered as a worst case profile.

To estimate the actual value to be used as P_{peak} in CONST profile, we performed an analysis of data from real devices. For the servers, we analyzed the performance metrics from different vendors and equipped with different CPU models³, and we computed 750W as the mean of peak values over a sample with more than 500 servers. For the switches, we computed the average values based on the datasheets of major vendors⁴, with optical fiber interfaces and compatible with OpenFlow protocol. For this analysis, we obtained 300W as peak value calculated from a sample of 30 switches.

3.4 Communication Model

A typical data center traffic can be categorized in two types: (a) traffic flowing between external systems and the data center, and (b) traffic exchanged internally to the data center. Even if a generic applications can generate both types of traffic, in the most common data centers usually one of the two traffic types is dominant.

For the scope of this paper, we consider applications with dominant intra data center traffic. The assumption is consistent as many real data center applications generate throughput-oriented workloads, which require bandwidth-intensive communications between the servers. Examples are data mining and MapReduce applications. In particular our VM model is compatible with offline batch processing, in which VMs are not directly involved in serving end-user requests. As a result, the vast majority of the traffic produced remains inside the data center. According to [9] the 99.8% of traffic generated by this kind of applications remains confined within the data center. Interestingly, nearly 75% of the traffic is destined to servers in the same rack.

3. https://www.spec.org/power_ssj2008/results/power_ssj2008.html

4. <https://www.opennetworking.org/sdn-openflow-products?start=501>

Algorithm 2 Random generation of V VMs with attachment probability p

```

1: procedure GENERATE-VMs( $V, p$ )
2:   for  $v = 1 \dots V$  do
3:     for  $k = v - 1 \dots 1$  do
4:       if rand() <  $p$  then
5:         Connect VM  $v$  with  $k$  with a random bandwidth requirement
6:         break
7:       end if
8:     end for
9:     FIND-SERVER-FOR-VM( $v$ )
10:  end for
11: end procedure

```

Commonly intra data center communication patterns can be categorized as (i) **one-to-one** one VM communicates directly to another VM; (ii) **one-to-several** one VM communicates with several other VMs; (iii) **all-to-all** all the VMs communicate together. We consider a VM generation process modeling a mix of the (i) and (ii) patterns. The traffic between any pair of VMs is assumed to be bidirectional and the required bandwidth is chosen at random. If we define the degree of a VM as the total number of VMs with whom it is communicating, our VM generation process permits to obtain VMs with random degree.

We adopt the incremental approach shown in Algorithm 2 to generate V VMs and the corresponding traffic exchanged among VMs. We use an “attachment” probability p that each new VM is connected to one of the most recently generated VMs. In more details, we use geometric trials to find a single destination VM to which the new VM is connected. Note that, since any generated VM can be chosen later as destination for a newly generated VM, the degree of any VM can be larger than one, even if the average degree is always one. This allows us to distribute fairly the communications among all the VMs. Actually, the value of p gives the level of variance on the VMs degree. When p is close to 1, a chain of VMs is generated, each with a maximum degree close to one. Whereas, when p is small, the VMs are interconnected randomly, and the maximum degree is larger than one. In the case a new generated VM is not connected to a previous VMs (i.e. the loop in lines 3-8 is not interrupted by the break), the new VM is isolated with respect to the previous VMs and it starts a new group of VMs.

The advantages of our model are its simplicity, since it depends on a single parameter p , and its flexibility, since it allows to model also groups of VMs. Finally, a server is selected for each newly generated VM based on the code of Algorithm 1.

4 PERFORMANCE EVALUATION

4.1 Simulation Setup

We considered data center architectures that have been designed with homogeneous switches, i.e. with the same number of ports. This allowed us to compare fairly the different architectures for the same/similar size of the data center. All the ports are assumed to run at 40 Gbps and are logically split into 4 ports at 10 Gbps when connected to the servers. The computing servers are indeed equipped with a single port at 10 Gbps. We always assume a server oversubscription ratio equal to 3 in all the DCNs, coherently with the design guidelines by Google in [14].

TABLE 1
Definition of the scenarios based on a 3-Tier architecture

SCENARIO	SERVERS	SWITCHES			
		SIZE	TOR	AGGREGATION	CORE
micro	96	4 ports	8	4	2
small	384	8 ports	16	8	4
medium	1536	16 ports	32	16	64
large	6144	32 ports	64	32	16
xlarge	13824	48 ports	96	48	24

TABLE 2
EPE index for a 3-Tier data center

POLICY	SCENARIO				
	micro	small	medium	large	extra-large
MNP	0.0073	0.0025	0.00082	0.00056	0.00020
SSC	0.0086	0.0035	0.00079	0.00038	0.00037
RSS	0.31	0.28	0.27	0.24	0.23

4.2 Results

We assess the property of energy proportionality of a data center in function of the load, the size and the layout of the DCN. We assume a CONST power function for all the nodes (servers and switches), since it provides a worst-case scenario to evaluate the energy proportionality of the overall data center. Indeed, in the case of FEP and REAL power profiles, the level of energy proportionality cannot be worse than the one provided by CONST.

4.2.1 Performance for a 3-Tier architecture

We start by considering specifically a 3-Tier architecture. Later, in Sec. 4.2.2, we will show that all the qualitative results obtained in this preliminary investigation hold also for 2-Tier and Jupiter DCNs. We consider specifically five different data center sizes, ranging from 96 servers to nearly 14 000 servers, built according to the specifications given in Tab. 1.

We investigate the three allocation policies RSS, SSC and MNP described in Sec. 3.1. Fig. 3a shows the impact of the policy on the power consumption in a small data center. The consolidation policies (MNP and SSC) appear to behave similarly and in an energy-proportional way, since they approximate well a FEP power profile. Conversely, the RSS policy, which aims at achieving load balancing, performs worse than the consolidation policies. This is due to the fact that distributing the VM workload across the servers activates a large number of servers regardless of their current load. As a consequence, servers with high or low loads share equal possibilities to become destination of an incoming VM.

Fig. 3b focuses on the network power consumption. The results obtained are similar to the the previous case: consolidation policies (MNP and SSC) make the network power consumption more energy proportional than the policy aiming at balancing the load (RSS). In particular, the graph clearly show that the difference between power consumption of network-aware (MNP) and network-oblivious (SSC) consolidation policies is minimal.

To understand the specific contribution of computing and networking equipment on the total power, Fig. 4 shows the total power, the power due to the servers and the power due to the switches, in function of the load. All the curves appear to approximate well an ideal energy proportional curve, regardless of the data center size. Only the network power for the smaller networks shows a more discontinuous curve, due to the small number of involved networking devices. This behavior is exacerbated by the CONST power profile considered in our simulations.

Figs. 5-7 show the PPVM index under different loads, different data center sizes and different allocation policies

respectively. The main message in Fig. 5 is that all the curves converge to the same value, which means that the operational costs due to power become constant *independently* from the size of the data center. Only when the load is very small, the PPVM shows slightly different behaviors. Fig. 6 shows the effect of the data center size and shows that the PPVM is almost independent from the switch size, and only for low loads and small data centers the value of the PPVM index is higher. When comparing the effect of the allocation policy, Fig. 7 shows that all the policies show a constant value independently from the size of the data center, and RSS achieves a PPVM equal to 270 W per VM, i.e. about 7 times larger than consolidation policies.

We evaluate also the blocking load and observe that it slightly increases with the data center size, varying between 0.92 in a micro data center and 0.94 for the xlarge one. This increase is due to the higher number of resources available in the latter scenario, but no meaningful difference was observed in all the other scenarios.

To assess quantitatively the effect of the data center size on the energy proportionality, we compute the EPE index on the total power. Fig. 4(a) shows the corresponding results for a load in the interval $[0, 0.90]$, i.e., smaller than the blocking load. Tab. 2 shows EPE for different sizes and for different allocation policies. Based on these results, we can claim that larger data centers are more energy proportional, independently from the adopted policy and layout. This is due to the larger number of computing and communication resources, which permits a more gradual resource commitment in function of the load. As observed before, when comparing the policies, the ones that consolidate the workload (i.e. MNP, SSC) achieve better energy proportionality than the ones that distributed the workload (RSS). Furthermore, MNP and SSC behave very similarly, and none of them is outperforming the other.

Finally, we compare the power efficiency of the network by computing the NPE index. The results in Fig. 8 show that the power efficiency is strongly influenced by the policy and the size of the data center. When increasing the data center size from micro to xlarge, the NPE decreases by a factor 10. RSS is around $5 \times$ less efficient than the consolidation policies. The MNP policy slightly outperforms SSC since it minimizes the network consumption by construction. Nevertheless, the gain of MNP with respect to SSC is small. Therefore, both consolidation policies are very robust in terms of power efficiency.

4.2.2 Comparison between different DCN

We now compare the energy proportionality of all the considered DCN layouts, including 2-Tier, 3-Tier and Jupiter. We always assume MNP allocation policy, as example of

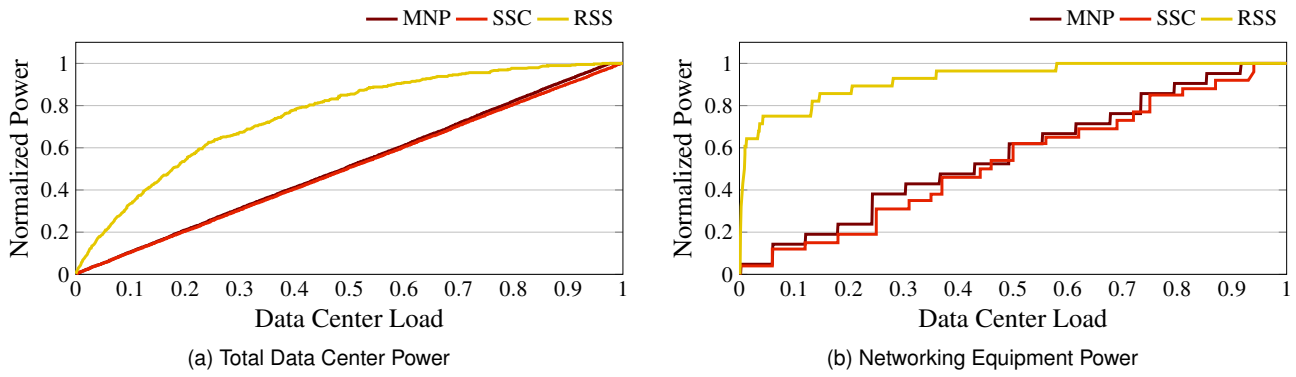


Fig. 3. Normalized Power consumption of different allocation policies aiming at consolidation (MNP, SSC) and load balancing (RSS)

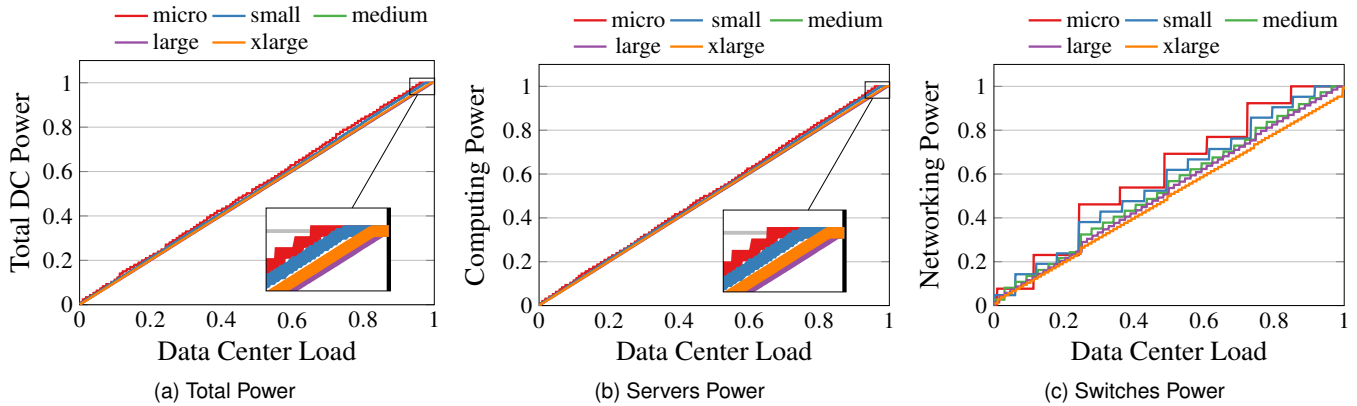


Fig. 4. Power consumption for different size of a 3-Tier DCN under a MNP policy

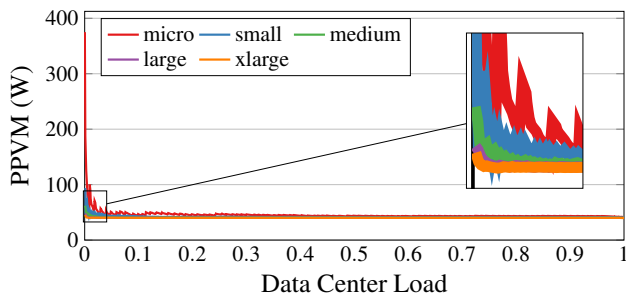


Fig. 5. PPVM for a 3-Tier DCN, under MNP policy and for different data center sizes

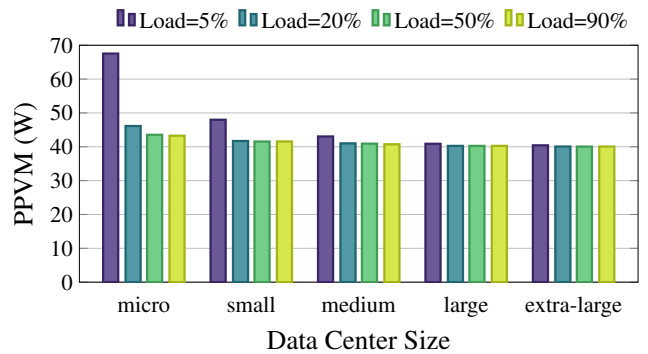


Fig. 6. PPVM for a 3-Tier DCN, under MNP policy and for different data center loads

TABLE 3
Data Center Networks

ARCHITECTURE	EQUIPMENT		
	SERVERS	SWITCHES	PORTS
2-Tier	5808	55	2420
3-Tier	6144	112	3584
Jupiter	6144	256	4096

consolidation policy. The settings for the considered scenario are reported in Tab. 3, according to which we approximately fix the size of the data center to host around 6,000 servers, which corresponds to a large data center. The actual number

of nodes (server and switches) has been chosen based on the peculiarity of the considered DCN.

Fig. 9 compares the PPVM index for different loads and different DCNs. Interestingly, all the DCNs shows the *same* PPVM, independently from the load. Thus, we can claim that the operation cost due to power is equivalent among the different DCNs, and thus simple to estimate experimentally. Notably, for the specific (but realistic) power model we considered in our simulations, PPVM is around 40 W per VM, the same value observed in all the scenarios considered for 3-Tier layout in the previous Section 4.2.1.

We now compare the EPE index to precisely assess

the level of energy proportionality. The numerical results show that the three DCNs behave almost as ideally energy proportional: the 2-Tier scores 0.00038, the 3-Tier 0.00057, and Jupiter 0.00055. As a conclusion, we can claim that all the three DCNs perform almost ideally in terms of energy proportionality, independently from the size and load, given that a consolidation policy is adopted.

5 DISCUSSION

The methodology illustrated in this paper is positioned to become an essential tool for data center operators to optimize management of existing facilities, to plan capacity extensions and to design future data centers. To illustrate, the operators willing to expand the capacity of existing facilities can easily assess the scale of the extension. Having determined the grade of energy proportionality in the facility, the forecasted loads to be supported and the implemented resource allocation policy, it becomes straightforward to decide the amount of resources that are required to upgrade the facility satisfying the tradeoff cost/revenues, expressed in terms of the number of VM it is possible to accommodate and the required power to provision the service. It is worth to highlight that the model takes into account VMs with heterogeneous requirements in terms of CPU, memory, storage and communication.

During the design phase of a new data center facility, the presented methodology could provide the operator the necessary information to decide the configuration of the DCN, including the number of its components to satisfy a given level of energy proportionality. For example, Table 4 illustrates the set of indexes EPE, PPVM and NPE measured when the MNP allocation policy is employed and under an offered load of 50%. The comparison analyzes different sizes of the planned DCN and the values obtained are a summary of the results presented in Section 4. We would like to recall that, the higher is the energy proportional profile of the data center, the easier is the prediction of the sustained energy costs.

5.1 Migration of VMs

All the considered policies, including RSS, SSC and MNP, operate in an incremental way, by allocating one VM at the time and never back-tracking on past decisions. Clearly, this

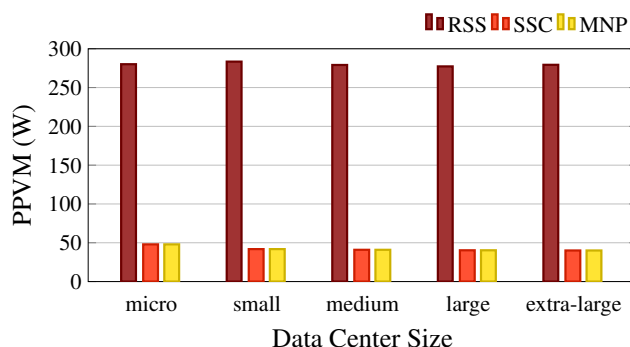


Fig. 7. PPVM for a 3-Tier DCN and data center load equal to 15%, under different allocation policies

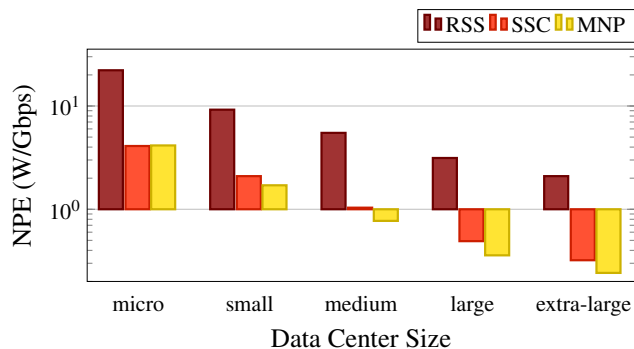


Fig. 8. NPE for a 3-Tier DCN and for different allocation policies.

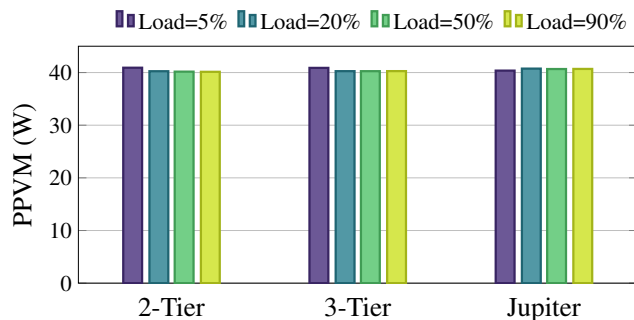


Fig. 9. PPVM for large data centers, under MNP policy

may lead to suboptimal solutions with respect to the results achievable when migration is allowed for already allocated VMs [24]. Nevertheless, the spirit of our contribution is to investigate the asymptotic behavior of very large data centers, and we claim that in such a scenario the effect of migration is practically negligible.

Indeed, assume for the sake of simplicity that VMs allocation is performed on the sole basis of their demand for CPU resources. Assume now that the servers support a maximum CPU capacity c_{max} and that, at time t a VM arrives with a normalized CPU requirement equal to α . Specifically, $\alpha = 1$ when the VM demands for c_{max} CPU resources, while the minimum demand for CPU resources is denoted as α_{min} . Consequently, $\alpha \in [\alpha_{min}, 1]$.

Let $S_{no-migration}(t)$ be the number of *active servers* at time t when migration is not allowed. Active servers are those serving at least one VM. Let $S_{migration}(t)$ be the number of active servers at time t when migration is allowed. Assume $w_{tot}(t)$ to be the total workload in terms of requested CPUs for all the VMs arrived up to time t .

TABLE 4
Performance of 3-Tier data center for MNP allocation policy

SIZE	TOTAL NODES	PERFORMANCE METRICS		
		EPE	PPVM (W)	NPE (W/Gbps)
micro	110	0.00732	43.2	4.150
small	412	0.00253	41.5	1.707
medium	1 592	0.00082	40.7	0.772
large	6 256	0.00056	40.2	0.358
xlarge	13 992	0.00020	40.0	0.242

We consider now a consolidation scheme that tries to pack all the new arriving VMs into the minimum number of servers (as the SSC policy). When migration is not allowed, for sufficiently large values of t , most of the servers will be singularly loaded for more than $c_{\max}(1 - \alpha_{\min})$. Indeed, VMs demanding small amounts of CPU resources have high probability to arrive and occupying the unused CPU resources of active servers. The bound can be expressed as follows:

$$S_{\text{no-migration}}(t) < \frac{w_{\text{tot}}(t)}{c_{\max}(1 - \alpha_{\min})}. \quad (5)$$

Instead, when migration is allowed, all the VMs can be reorganized at any time and exploit the unused CPU resources of active servers. As a result, all the active servers will be fully loaded in the optimal case. Thus,

$$S_{\text{migration}}(t) \geq \frac{w_{\text{tot}}(t)}{c_{\max}}. \quad (6)$$

Comparing the number of active servers in the two scenarios:

$$\frac{S_{\text{no-migration}}(t)}{S_{\text{migration}}(t)} < \frac{1}{1 - \alpha_{\min}} \approx 1 + \alpha_{\min}, \quad (7)$$

where the last approximation holds since α_{\min} is usually much smaller than 1. Indeed, the minimum CPU request is very small (e.g. 1 CPU) with respect to the available CPUs (e.g. 32-40 CPUs) available in data center servers.

According to (7), the expected effect of allowing migration is to decrease the power consumption of a factor $1 + \alpha_{\min}$, which is quite small in practical cases and thus can be neglected. Note that the current analysis on the effect of migration relies on two fundamental assumptions: (i) our work provides an asymptotical analysis on energy proportionality for large data centers and for sufficiently large amounts of time (which guarantee to fill almost all the servers), (ii) the CPU requirement of a VM is fixed and does not vary during runtime. The last assumption is coherent with the standard practices in IaaS cloud computing environments [25]. OpenStack allows the users to specify the configuration of the VM. Specifically, the configurations, also known as “flavors”, are uniquely identified by virtual CPUs, disk and memory of the VM [26]. Amazon EC2, provides a pre-configured pool of VM sizes similarly to OpenStack, called “Instance Types” [27]. Once selected, the configurations cannot be changed during runtime, hence any upgrade of resource demands requires the VM to be first destroyed and then re-created with the new requirements.

6 RELATED WORKS

This section reviews the research in the field of DCNs and related works on energy proportionality in data centers.

6.1 Background on Data Center Networks

In literature, DCNs are typically attributed to two different categories: *switch-centric* and *server-centric* [28], [29], [30], [31]. A switch-centric network is composed of communication nodes (i.e. switches and routers), which forward packets, and computing nodes (i.e. servers) which send and receive packets. In a server-centric network, instead, computing nodes are also in charge of packet routing and forwarding,

acting as software routers. Despite in the recent years a number of server-centric DCNs were proposed, including BCube [32], DCell [33], FiConn [34] among the others [29], [30], practically they are not implemented. The main reason is the high cabling complexity and the large management costs [14]. Recently *dual-centric* DCNs have been proposed in [35]. These DCNs provide flexible choices in designing layouts and promise to achieve various trade-offs between performance and power consumption, placing routing intelligence on both switches and servers.

Although *dual* and *server-centric* are very promising designing layouts their adoption in real data center is still quite low, thus our analysis focuses on widely-adopted switch-centric networks, derived by traditional 3-stage Clos networks. A Clos network [36] is a modular multistage switching network, based on the interconnection of small-size switches, providing full bisection bandwidth. Notably, the bisection bandwidth is proportional to the number of active core switching modules, thus in case of failures the overall performance degrades smoothly.

Unlike the majority of the works in the literature, one of the strengths of our methodology is in the integrated analysis of the power consumption of the two components of a data center: the computing equipment (servers) and the communication equipment (switches). This choice stems out from a fundamental consideration. Cloud applications are composed by highly distributed components, generating both traffic and computing requests that impact on communication and computing consumption of the data center [37]. Therefore, it becomes essential to consider the effect of different allocation policies, which define the rules of assignment of a VM to a computing server. Indeed, allocation directly influence power consumption. Fig. 3b shows that two different allocation policies, both oblivious of the network (SSC and RSS), have different impact on the network consumption: the first is more energy proportional than the latter. In literature many research works aimed at optimizing performance and energy efficiency of allocation policies in DCNs [38], [39], [40]. However, at the best of our knowledge, none of them has analyzed the impact of allocation policies on the joint consumption of computing and communication, and how they affect each other for different DCNs. Moreover a study on the relation between scalability and energy consumption is still missing, and in this paper we aim at filling this gap.

6.2 Research on energy proportionality

Energy proportionality was first introduced in 2007 by Barroso et al. as a fundamental property of a device, or a system, which consumes energy in relation to the amount of work performed [13]. At that time the focus was on the most power-hungry component of the data center, i.e. the servers. But with the advent of technologies like DVFS (Dynamic Voltage and Frequency Scaling) servers became more energy proportional and more attention has been placed on switches and network consumption. To the best of our knowledge, so far ideally energy-proportional commercial switches do not exist, more precisely the power profile of these devices does not consume any power under zero load and it increases linearly with the load, reaching the power peak under the

maximum load, as described in Sec.3.3 about FEP profile. However, scientific community widely investigates solutions to make more energy proportional the network [2], [41], [42], [43], [44], [45]. While in the majority of the cases energy proportionality has been investigated to understand the energy profile of each single device, in our work the energy proportionality has been used as a metric to assess energy efficiency of whole DCNs, comparing different layouts, sizes and allocation policies.

Almost all the works found in literature investigate energy proportionality analyzing network consumption independently from the consumption of the computing components [2], [41], [42], [43]. But, as we demonstrate, the VM allocation policy onto servers has an impact on the network consumption, and thus energy proportionality analysis cannot be done independently (see Fig. 3b).

In [2] the energy proportionality of a network was analyzed through a theoretical comparison of two highly scalable networks: a flattened butterfly and a folded-Clos. The authors did not evaluate the consumption in function of the load, but compared the two networks based on a fixed value of the bisection bandwidth. This is a remarkable difference with respect to our work since we argue that the consumption is influenced by the allocation policy used to load the data center, as explained in Sec. 2.2.

In [41] the use of energy-proportional routers was proposed to connect different data centers. A green energy-aware routing algorithm was simulated, achieving a 10× improvement in energy efficiency respect to traditional solutions. Thus, that work focused on increasing the energy efficiency of a backbone network while our interest is to investigate energy proportionality in DCNs.

The work in [46] proposed to replace high-radix switches with many tiny low port-count switches called NoTS (Network of Tiny Switches). Indeed, switches with lower forwarding rates achieves higher levels of power efficiency (in terms of W/Gbps) and are more energy proportional. The paper shows that deploying a large number of tiny switches enables devices to be turned off with finer granularity, thereby allowing the entire network to be more power proportional. ElasticTree [42] proposed an advanced power management, which dynamically adjusts the set of links and switches to satisfy changing in loads, minimizing energy consumption. It continuously monitors the traffic of the data center and chooses the set of network elements to activate to meet performance and fault tolerance requirements. Then it powers down as many unneeded links and switches as possible. Both [46] and [42] neglected to consider the effect of the size of data centers and of the DCN layout.

In [43] a new approach was proposed to design a DCN, based on choosing the optimal switch size that can potentially save the most power during the expected operation of the network. The scope of the work was limited to Fat-Tree topologies, with different tiers by same number of supported servers.

The work in [44] studied different techniques to reduce the operational network energy in data centers and enterprise networks. It considered specifically consolidation techniques operating directly on switches (e.g. sleep mode, rate-port adaptation) and on servers (e.g. wake-up on line, keep-alive proxy). A combination of the two techniques was

shown to lead to a 74% of energy savings, but at the cost of availability and reliability. However the proposed solution requires an oracle knowing in advance the traffic pattern. Furthermore only a small data center composed by 300 server was considered.

The Energy Proportionality Coefficient (EPC) was proposed to assess quantitatively the degree of energy proportionality of a device or a system in [21]. The EPC index is defined in the interval $[0, 1]$ and it is based on the deviation of the normalized power curve $f(x)$ in function of the normalized load x with respect to the ideal case, corresponding to a straight line with constant slope. Being α the angle of the the tangent in a point of the observed curve, the EPC can be calculated as follows:

$$EPC = \int_0^1 \sin 2\alpha(x) dx,$$

where $\tan \alpha(x) = df(x)/dx$. By construction, a perfect energy-proportional system shows $EPC = 1$. However, this index cannot be used for discontinuous functions, which describe the power consumption of the data center analyzed in this works. For this reason, in the current paper we propose a new index, called EPE and defined in Sec. 2.2.

7 CONCLUSIONS

Probably in the future, small and medium data centers will be dismissed and workloads consolidated on single data centers, to benefit from economies of scale. Moreover the bursting nature of the cloud workloads force operators to over-provision data centers to support sporadic spikes of demand. Therefore, mega data centers containing hundreds of thousand of servers and switches are becoming essential. They have a potential to increase the performance dramatically at the cost of power consumption. Consequently, consistent research efforts in DCN domain are undergoing. New DCNs should be scalable to support huge number of servers and energy efficient to contain costs.

In this paper, we focus on the concept of energy proportionality applied to the whole DCN. Energy proportionality is a property defining the degree of proportionality between load and the energy spent to support such load. A peculiar feature of our analysis is in the consideration of the whole data center, i.e., both computing and communication devices are taken into account. Our methodology consists of an asymptotic analysis of data center consumption, whenever its size (in terms of servers) become very large. We compared the energy performance of different DCNs under different scenarios, varying the size (from 96 to almost 14,000 servers) and the allocation policy (including two consolidation and one distribution policies). The considered DCNs were 2-Tier, 3-Tier and Jupiter, the latter being adopted by Google. The metrics used for the comparison allowed to analyze the energy proportionality of both computing and communication components (EPE index), the energy cost spent to allocate each incoming VM at various utilization levels of the data center (PPVM index) and the efficiency of the network expressed in terms of energy consumption per bit of delivered information (NPE index). These indexes were conceived specifically for our investigation, overcoming some limitations of the previous metrics.

In our results we showed that the specific layout of the data center does not impact the energy proportionality, since all the DCNs achieves the same EPE under different loads. Considering the scalability of data centers, we showed that large data centers are more energy proportional. Thus we can claim that the energy proportionality is mainly driven by the number of elements of the data centers, and it is agnostic respect the layout and the adopted allocation policy. Moreover, the size and the layout of the data center do not impact on the PPVM which converge to the same value of 40W per VM. The efficiency of the network (NPE) instead, is strongly influenced by the size and the adopted allocation policy. Our results showed that the NPE decreases by a factor of 10 when the size of the data center increases.

Future directions envision the extension of the comparison with server-centric DCNs, which are gaining interest in the data center field. Further extension can include the comparison with more DCNs and the implementation of more realistic communication models with the possibility to move the workload of the server throughout the migration of VMs.

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