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Virtualization and consolidation: a systematic review of the past 10 years of research on energy and performance

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Abstract
This survey is an up-to-date account of the research on the performance–energy trade-off in virtualized environments, specifically in virtual machine consolidation. The factors that influence the performance and energy in consolidated data centres and the performance–energy trade-off itself are analysed. Based on these factors, we propose a categorization that classifies the most important research on performance and energy in consolidated systems. We have analysed and summarized 91 selected research works from an initial set of 1030. This article summarizes all previous surveys on the subject of virtual machine consolidation and updates them with the most recent papers in the field.

Keywords Virtualization · Virtual machine consolidation · Performance degradation · Energy efficiency · Performance–energy trade-off

1 Introduction

Computer complexity has increased in recent years, resulting in the necessity to manage the complexity through system abstraction levels design. In this type of design, levels are separated and connected by interfaces. The levels of abstraction are organized in a hierarchy, where the lower levels are implemented in hardware and the higher ones in software. The hardware levels are composed of physical devices that have real features, and their interfaces aim to connect the physical devices with other

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devices. In the same manner, the software levels are composed of logical entities that are restricted by hardware-level properties [80].

Implementing virtualization technology is a way to relax the physical hardware constraints and increase a system's flexibility. Virtualization provides an abstract and isolated environment to execute applications, and there is a large set of technologies and concepts that enable it. The most common use for the term virtualization is associated with hardware, such as the infrastructure-as-a-service (IaaS) solution for cloud computing [19].

Virtualization provides a set of functionalities, such as the abstraction of hardware resources and simpler access. Additionally, it enables users to be isolated from one another and supports virtual instances replication, increasing the elasticity of a system.

Renewed interest in virtualization technologies has emerged due to the increase in the resources of servers, as well as their low resource usage, the limitations of the physical space in data centres, greening initiatives and management costs [19].

Due to the rise in cloud server utilization, virtualization is gaining increasing importance in running multiple servers on a single shared infrastructure. This technique is known as virtual machine consolidation. Furthermore, virtualization promises cost savings, but the adoption of server virtualization implies an increase in system complexity. Additionally, virtual machines have lower performance than that of equivalent physical machines executing the same workload [80].

Currently, it is crucial to account for the energy and power consumption of data centres, which is a concern for most companies. The total share of electricity consumed by the world's data centres has reached 0.5%. Moreover, data centres are responsible for more carbon emissions than North America and the Netherlands combined. This high level of energy consumption is explained by an inefficient use of the resources, despite the efficiency in the power consumption of the hardware [33].

Our interest in this survey is to assess research studies on maximizing performance and greening initiatives supported by virtual machine consolidation from 2009 until 2018. Virtualization allows data centres to manage resources and to create several virtual machines in the same physical machine to improve energy inefficiency. Each virtual machine represents a run-time environment (one user) that is completely isolated. Virtualization reduces power consumption by switching off idle physical machines while preserving the customers performance requirements [17].

As mentioned above, one drawback of server virtualization is the increase in system complexity due to the introduction of a virtual machine manager (VMM) or hypervisor. The VMM is a piece of software allocated between the physical resources and applications. The main function of the VMM is to manage the virtual machines [17]. It is important to note that a virtual machine often provides lower performance than that of an equivalent physical machine running the same workload [56,86]. Moreover, the power consumption of these physical machines has increased due to the growth in virtual server utilization. As a result, new performance and energy management challenges in consolidated data centres have been introduced.

This work gathers the latest advances in research on performance and energy consumption in virtual machine consolidation. We analyse those concepts from the perspectives of the performance, power consumption and energy consumption of consolidated data centres. Consequently, the categorization of related works on the performance and energy-influencing factors inherent to virtualization is presented.

This paper is organized as follows. In Sect. 1, we introduce the aim and the scope of this work: the past ten years of the state of the art of performance–energy trade-off in virtual machine consolidation. Then, in Sect. 2, we present the methodology that we applied to perform the systematic literature review. In Sect. 3, we classify the state-of-the-art virtual machine consolidation techniques. In Sect. 4, we discuss the main concepts related to virtualization technology and virtual machine consolidation. In Sects. 5, 6 and 7, we study the factors influencing the performance, energy consumption and energy–performance trade-off in virtual machine consolidation. Additionally, we propose a categorization for each class of influencing factors. In Sect. 8, we propose a categorization of the past ten years of research in virtual machine consolidation, taking account the previously proposed categorization. In Sects. 9 and 10, we discuss the most relevant findings related to virtual machine consolidation energy, performance and their trade-off and conclude the paper.

2 Systematic literature review methodology

The aim of this paper is to present the past ten years of research on the performance–energy trade-off in virtual machine consolidation. A systematic literature review is necessary to achieve this aim. A selection process is defined and performed to study a large part of the most relevant virtual machine consolidation literature. This section presents a detailed description of the literature selection process based on [35,52,79].

2.1 Keywords search

The process of selecting relevant articles starts with a search of research articles in the Google Scholar database using the following keywords in the article title: “virtualization”, “performance”, “consolidation”, “energy”, “power”, “energy efficiency” and “tradeoff”. Specifically, the keywords are described by the following logical expression: “virtualization” AND “performance” AND “consolidation” AND (“energy” OR “power” OR “energy efficiency” OR “tradeoff”). The logical expression was evaluated from 2009 to early 2018, resulting in a total of 1030 available research works.

2.2 Abstract and publisher filtering

Considering the 1030 articles resulting from the keywords filtering, an abstract reading was performed to identify only the most relevant articles that specifically addressed the performance–energy trade-off in virtual machine consolidation. After the abstract reading, 90 research papers were selected.

It is important to highlight that in selecting these 91 articles, we took into account the editorial and publisher; that is, the literature selection process was focused on articles from relevant publishers, such as Elsevier, Springer, IEEE and ACM. Figure 1 shows the per cent of articles from each publisher. The publishers with the most selected

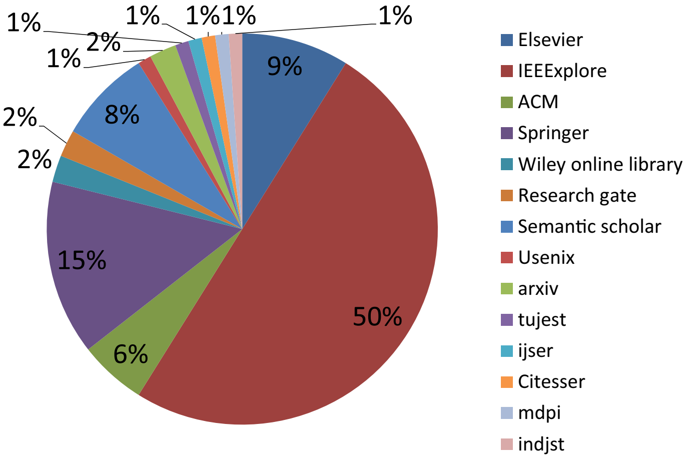

Fig. 1 Distribution of articles per publisher

Table 1 Distribution of research works over the past 10 years

Year	Number of selected works (%)	List of research works
2009	1	[18]
2010	4	[4,92,101,102]
2011	6	[16,54,57,59,63,64]
2012	16	[22,32,42,43,48,53,58,81,88,97–100,108]
2013	13	[21,23,29,31,34,37,39,47,51,66,82,83,104]
2014	18	[6,10,24,33,40,45,50,61,65,72,78,87,89,95,103]
2015	23	[1,2,7–9,28,30,36,46,60,62,69,74,76,77,94,96,105,106,109]
2016	11	[5,27,38,41,55,68,75,84,90,91]
2017	5	[11,25,67,73,107]
2018	3	[15,26,85]

papers are (1) IEEE, (2) Springer, (3) Elsevier and (4) ACM. Additionally, the time distribution of the selected articles is presented in Table 1. From 2009 to 2015, the number of published articles increases as the performance–energy trade-off became a popular topic in computer science research. After 2015, the number of articles goes down.

2.3 Topic distribution of the selected papers

Many of the research works are devoted to analysing more than one topic. Figure 2 shows the three topic classes we selected: performance, energy and performance–energy trade-off. Some research works focus on only performance or energy topics, but the rest are devoted to simultaneously analysing performance and energy or energy and the performance–energy trade-off.

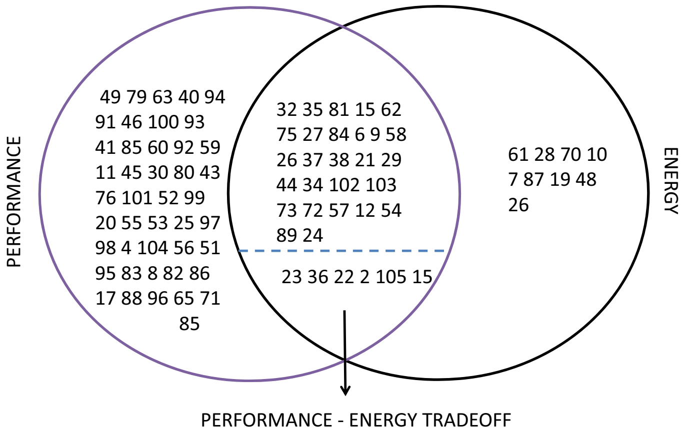

Fig. 2 Overlap between topics

3 State of the art in virtual machine consolidation techniques

Several classifications of performance and energy consumption in virtual machine consolidation exist in the literature. We summarize these classifications in this section.

In [94], the authors propose a classification of virtual machine consolidation techniques based on different parameters, including the decision-making time, the system parameters, the optimization method in terms of the objective function and the evaluation method. The decision-making time is the time needed by the consolidation method to allocate the virtual machines in the physical nodes. This time can be static or dynamic, taking into account the variation in the workload. The system parameters refer to the physical machine features, such as hardware utilization, the network traffic, the cooling systems, the performance impact, the system reliability and the migration overhead. Depending on these parameters, the consolidation technique is constructed in different ways. The optimization method refers to the algorithm implementation, for example, exact methods, heuristics and meta-heuristics. The objective function defines the goal of the consolidation technique, such as minimizing the number of active hosts, minimizing the SLA violations, minimizing the response time, maximizing the reliability and maximizing the resource utilization. Finally, the consolidation techniques are classified by the evaluation method, that is, simulation or real experimentation.

In a similar manner, in [3], the authors propose a categorization for server consolidation frameworks. This categorization is based on different parameters such as resource assignment policy, the system architecture, the virtual machine allocation criteria, the migration triggering point and the model. The resource assignment policy refers to the capacity to assign resources to virtual machines in a dynamic or static manner. The architecture is the distribution of the physical machines (centralized or decentralized). The co-location criteria are the variables that the system administrator wants to optimize, such as the affinity of the system, the resource utility and the power consumption. The migration triggering point is the information that the consolidation technique uses to make a decision, such as historic data, scheduled adoption or heuristics. The last parameter is the migration model, which can be pre-copy or post-copy.

Moreover, in [49], the authors present a group of surveys on virtual machine consolidation algorithms, which can be classified in two groups: dynamic virtual machine consolidation (DVMC) and static virtual machine consolidation (SVMC) algorithms. In DVMC algorithms, the system receives workloads that will be run on virtual machines, and these virtual machines perform the assigned workload and consume the respective physical resources. In these algorithms, the current virtual machine assignment to physical servers is taken into account in the consolidation process. In contrast to DVMC algorithms, SVMC algorithms do not take into account the current virtual machine assignment to physical machines when a new physical machine is chosen for any virtual machine.

The DVMC algorithm is applied when the physical server already allocates the virtual machines, and it is performed during run-time. DVMC algorithms can be classified by different criteria. First, they can be divided into two classes: centralized DVMC algorithms and distributed DVMC algorithms. Moreover, DVMC algorithms can be classified based on different source physical machine selection techniques, such as threshold-based DVMC algorithms, threshold-free DVMC algorithms, static threshold-based DVMC algorithms and adaptive threshold-based DVMC algorithms. Moreover, DVMC algorithms can be classified based on the virtual machine selection policy: clustered virtual machine selection and single virtual machine selection. Taking into account the consideration of estimated future resources, DVMC algorithms can be classified as non-predictive dynamic virtual machine consolidation algorithms or predictive dynamic virtual machine consolidation algorithms. Based on the destination physical machine selection strategy, DVMC algorithms can be classified as random physical machine selection, greedy heuristic, best fit, best fit decreasing, power-aware best fit decreasing and meta-heuristics. Finally, DVMV algorithms can be classified based on the objective, such as SLA violation aware, security aware, network efficiency aware, network efficiency aware, data centre energy aware and cache contention aware.

A variety of techniques to improve the energy efficiency in the virtual machine consolidation environment have been proposed. In [68], the authors proposed a classification of virtual machine consolidation techniques in an energy-aware context. The classification contains the following classes: fault-tolerant migration techniques, load balancing migration techniques and energy efficient migration techniques. The first refers to techniques that shift (or migrate) virtual machines between physical servers depending on the assumption of the fail. The second refers to those techniques that aim to evenly distribute the workload of the system to improve the scalability of the cloud environment. The last refers to techniques that aim to improve the energy efficiency in cloud data centres.

As we explained previously, the proposed classifications are based on either performance-influencing factors or energy-influencing factors. Moreover, researchers have studied virtual machine consolidation techniques from an implementation perspective, including algorithms, techniques and frameworks. However, to the best of our knowledge, this is the first attempt to study the virtual machine consolidation factors that affect the performance–energy trade-off and to propose a classification of literature based on these factors.

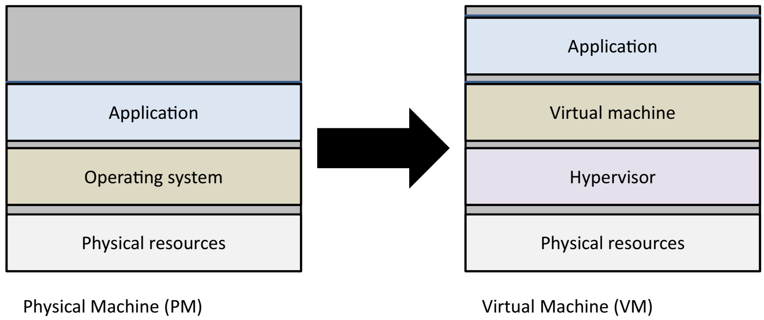

Fig. 3 From a traditional data centre to a virtualized one based on [17]

4 Virtualization technology and virtual machine consolidation

Traditionally, the solution for deploying a data centre was to outfit the physical servers with a standard operating system and to rely on these operating system techniques to ensure the resource sharing, security and performance isolation. From the service provider perspective, there were some challenging issues: system, account, security and resource management. In the same manner, application development and performance optimization were challenging for the users. Virtualization technology was developed to address the challenges faced by systems administrators and users.

Virtualization is a set of enabling technologies and concepts that provide an abstraction and isolation of the application execution environments. The term virtualization often refers to hardware virtualization. Throughout the history of computer science, virtualization technologies have a long trail and have been adopted at many architectural levels, such as operating system, programming language and application. Moreover, virtualization technology can be applied to different components, including storage, memory and networking, not only at the application level.

In the last few years, virtualization technology has received growing interest because of the increase in computer performance and their underutilized conditions, in addition to other features, such as the rise of green computing and the lack of space in data centres. Specifically, green initiatives are often implemented through virtual machine consolidation.

Virtualization technology can be generally defined as the instantiation of a logical instance of hardware, such as computation, storage or network. A virtual environment is composed of three major entities: guest, host and virtualization layer. The guest interacts with the virtualization layer, rather than with the host, and represents the system's components. The host corresponds to the low layer, or the original system, which is able to manage and allocate the guest. The virtualization layer or virtual machine manager is a piece of software allocated between the physical resources and the applications. It is in charge of managing the virtual machines, that is, the creation, migration, cloning and deleting [83] (see Fig. 3). Guests are represented by a system image in the case of hardware virtualization.

As stated before, virtual machine consolidation, or server consolidation, is one of the techniques for greening data centres. This technique is based on the reallocation

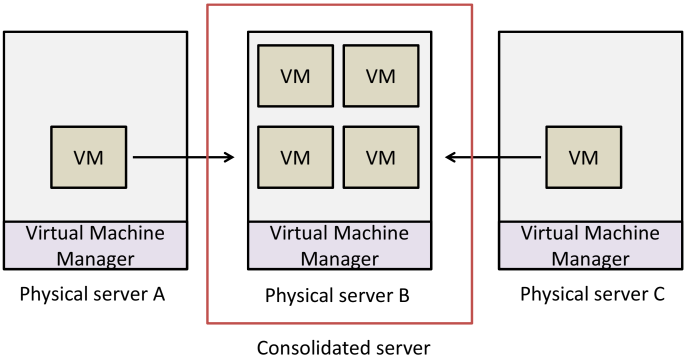

Fig. 4 Virtual machine consolidation

of virtual machines among different physical servers using virtual machine migration (see Fig. 4). As a consequence, the utilization of physical resource increases and the number of switched on physical servers decreases. The workload of a consolidated server can increase from 50 to 86%. At this utilization level, servers operate more energy efficiently [82].

The consolidation of virtual machines increases the utilization of physical machines, and as a consequence, the power is reduced and the energy consumption may be reduced, depending on the overhead due to the virtualization. The overhead is the extra workload that the physical machine has to perform due to being virtualized. The load is related to the tasks of managing virtual machines and coordinating the access to physical resources from the virtual instances. As a consequence, the larger the number of consolidated virtual machines within the same physical machine is, the higher the overhead is because the hypervisor is in charge of managing and coordinating virtual machines that simultaneously demand different resources.

Therefore, performance degradation occurs due to the overhead of consolidating virtual machines in physical machines, despite the reduction in power consumption. Consequently, the reduction in energy consumption depends on both the performance degradation and power consumption.

5 Performance-influencing factors in virtual servers

This section studies the factors that influence performance in the field of virtualized systems, especially in consolidated data centres.

5.1 Performance-influencing factors in virtualization

Equivalent performance of physical and consolidated virtual machines is not required as a part of virtualization. This is due to the increase in system dynamics because there is no direct control over the hardware of the system and the complexity of the application and workload interactions when the same infrastructure is shared [44].

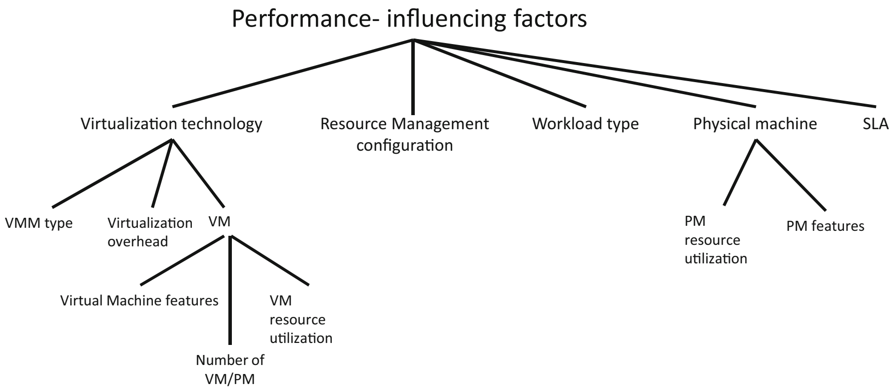

Fig. 5 Performance-influencing factors in a data centre

Despite the importance of the influencing factors in the degradation of performance in virtualization, there are few recent research works related to these factors. To the best of our knowledge, Huber et al. [44] is the first attempt to present the factors that influence performance in the case of virtualization. These factors are classified as virtual machine monitor type, resource management configuration and workload profile.

The virtual machine monitor refers to the layer between the physical hardware and the virtual machines that enables the creation and management of virtual instances [44]. Depending on the nature of the virtual machine monitor, the performance and energy consumption behave different. The research works (for a data centre or a single server) focused on virtual machine monitoring architecture aim to determine how the architecture influences the performance degradation. There is some related literature [86], but we will present the main research works in this field.

Regarding the resource management configuration, the allocated number of virtual machines and the scheduling determine whether the average performance improves. Generally, if the number of virtual machines per physical server increases, the resource management task performed by the hypervisor will be more complex.

Clearly, the nature of the executed workload affects the system's performance [44]. Therefore, the research works focused on this area attempt to study the effects on the performance of a specific workload to modify the workload features.

5.2 Performance-influencing factors in virtual machine consolidation

In the previous section, we discussed the performance-influencing factors in virtualized systems studied by Huber et al. [44]. Nevertheless, taking into account the virtual machine consolidation, there are new factors that affect system performance. These factors have been obtained in our previous experimentation, and they are classified, along with those proposed by Huber et al. [44], in Fig. 5.

These factors are virtual machine features, virtual machine resource utilization, physical machine resources utilization, physical machine features, device, virtualization overhead, number of consolidated machines, virtual machine interferences and the service level agreement (SLA).

Virtual machine features refer to the quantity of virtual resources that has been assigned to each allocated virtual machine in the virtual system, that is, the number of CPU cores, main memory size, hard disc size and network features. The performance of the virtual machine depends on these quantities. For both a data centre and a single server, studies aims to show the effects in terms of performance degradation related to the virtual machine features. Moreover, the virtual machine resources are another factor that affects the performance. The research studies related to this field quantify the degradation of the performance in virtualized systems with heterogeneous virtual machines. Other studies try to determine the virtual machine resource utilization that minimizes the performance degradation.

The physical and virtual machine resource utilization affects the physical machine performance, which varies depending on the utilization of physical or virtual resources. If the machine resource utilization is high, the physical resource demand increases. As a consequence, the physical resources are subject to a performance bottleneck.

The consolidation ratio is defined as the number of virtual machines per physical host. Some works have studied the optimal consolidation ratio to minimize the performance degradation [15].

The physical machine features affect the performance of the virtualized system. Here, the research works are focused on finding the optimal hardware for virtualization. Thus, the utilization of the resources of the physical machine also affects the system performance. These studies are related to the detection of an overloaded or underloaded physical machine to consolidate the virtual machine to optimize the system's performance.

Moreover, virtualization has inherent overhead due to virtual machine management. This performance overhead varies between systems that implement different features and execute different workloads [44]. Therefore, there are recent works quantifying the performance degradation caused by the system overhead and determining the resources of this overhead in order to minimize it.

Virtual machine interference refers to the performance degradation induced by the allocation of virtual machines in the same physical host. The aims of the studies in this field are to quantify the performance degradation and to find the factors related to virtual machine interference that cause this degradation.

In addition, we should consider that virtualizing resources results in performance overhead. It is not the same to virtualize a CPU and to virtualize network access. Different devices have different performance behaviour and power consumption models.

The last issue is the SLA, a critical components of cloud computing systems, which are supported mainly by virtualization technology. Nevertheless, the SLA could be violated due to the performance degradation inherent to virtualization. For this reason, there are studies on how to minimize the SLA violation rate while maintaining minimal performance degradation.

The influencing performance factors presented above refer only to a single physical server. Currently, data centres are composed of a large number of interconnected physical servers. The fact that such network connections exist affects the performance

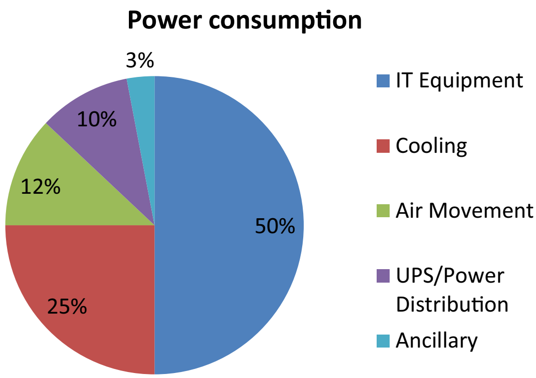

Fig. 6 Power consumption distribution in a traditional data centre, based on [13,17]

of the servers. That is, it is necessary to ensure that the servers perform in an appropriate manner not only individually, but also as a whole.

To ensure the performance in the server pool, the migration of virtual machines arose in such a way that the load could be balanced between different servers. There is a lot of literature regarding this technique [2], but this is not the subject of our work.

As a result, the influencing factors proposed above will be studied based on whether the system consists of a single server or a connected set of servers (see Fig. 5).

6 Energy-influencing factors in virtualization

Currently, data centres consume large amounts of power and energy, regardless of whether they are using virtualization. Energy consumption can be defined as the speed at which power (Watts) is consumed. In turn, energy is the sum of the power consumed during a certain period of time. In the particular case of the data centre, energy consumption is the speed at which the power is consumed by the physical servers [13]. The energy consumption depends not only on the power consumption of the physical machines, but also on the time when these machines are in operation (execution plus waiting time), that is, the response time of a given workload.

In a data centre, there are several sources of power consumption (see Fig. 6): 50% of the power consumption is related to IT equipment, followed by 25% from cooling systems, 12% from air ventilation and 10% from the power distribution system.

Taking into account that energy consumption is the power consumed over a period of time and that most of the power consumption comes from the equipment, we could infer that servers are one of the highest energy consuming components of a data centre. In turn, servers are the area where engineering should focus to maximize the energy efficiency.

Power reduction can be achieved through different techniques, such as lowering the CPU frequency. By contrast, energy reduction requires an analysis of the response time of the application; applications with longer execution times consume an extra amount of energy. Furthermore, reducing the peak power consumption reduces the provisioned infrastructure, but not the energy consumption [17].

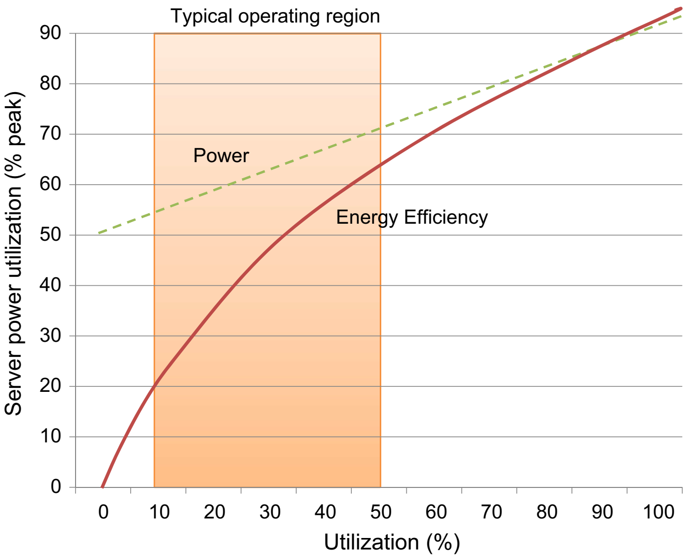

Fig. 7 Power consumption of a physical server as a function of resource utilization in an energy proportional system, as it appears in [14,17]

Many proposals address the reduction in power consumption in data centres, such as placing them in cold climate areas and managing resources in a more optimal way (to quantify and manage energy consumption and the energy efficiency [70]). Energy efficiency and power proportionality are two of the main metrics associated with power consumption. Energy efficiency is the ratio between system performance and its energy consumption [17]. Power proportionality, which establishes that the power has to be consumed in proportion to the work performed, is a desired property for any architecture [14]. However, this feature is not necessary for a system to be considered energy efficient. In the same way, if a system consumes energy in a proportional way, it does not mean that the power consumption is proportional. This is due to the variation in the workload of the system, which demands not only proportional energy consumption, but also power proportionality (see Fig. 7). The variation in power consumption is represented by the dotted line, and it is plotted as a function of system utilization. The system consumes half of the peak power when completely idle. Then, the system has poor power proportionality due to the increase in energy efficiency. The energy efficiency is very low for the low-use cases, and it increases as the utilization increases. Figure 7 also describes an ideal proportional system that keeps the energy efficiency at a constant level of 0.0 when the system is idle.

Specifically, in virtualized data centres, the energy consumption is higher than that in non-virtualized ones. As mentioned previously, virtualizing a physical server results in a performance degradation. This implies, on the one hand, an increase in the use of resources and, on the other hand, an increase in the response time of the workload being executed at a given moment. By increasing the use of resources, the power consumption also increases (see Fig. 7), and increasing the response time will increase the energy

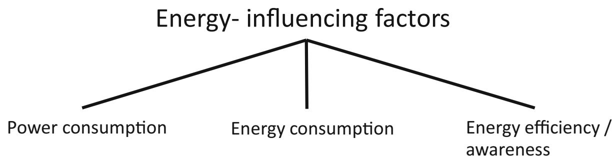

Fig. 8 Energy-influencing factors in a data centre

consumed for that particular task. Virtual machine migration, which enables physical machines to be turned off due to virtual machine consolidation, is used to diminish this phenomenon.

Therefore, the factors that affect the energy consumption in virtualization are the power consumption of the physical servers, the energy consumed by the physical servers and the energy efficiency of the virtualized system (see Fig. 8).

7 Energy–performance trade-off

So far, aspects such as performance and energy consumption in virtualized data centres have been analysed separately, that is, without taking into account the relationship between these two factors. Previously, we stated that virtualization causes performance degradation and, in turn, an increase in energy consumption. Nevertheless, virtualization provides data centres with a set of functionalities that make it possible to adapt to the requirements of current users.

However, when systems administrators consolidate virtual machines, they are reducing the power consumption of the data centre since there are physical machines that may be switched off or at least put on standby. Nevertheless, the workload of the physical machine host is then higher, so the performance is further degraded.

Therefore, taking into account this characteristic, the dual objective is to maximize the performance of the physical machine while minimizing the power and energy consumption. That is, it is necessary to find a trade-off between the energy consumption and performance of the physical machine. In certain cases, the energy saving is not compensated for with the performance, which will be very poor. It could also be the opposite case, that is, high performance of the data centre may not be able to compensate the energy consumption, and it is necessary to consolidate virtual machines to reduce it. Recent research works related to the optimization of these two issues separately or simultaneously have been conducted [2,49].

8 Proposed categorization

Throughout this work, we present the factors to consider when studying virtualized physical machines, such as performance, power, energy consumption and energy–performance trade-off. Moreover, whether the physical machine is isolated or connected should be considered.

We propose a categorization of the articles published based on two dimensions. The former is the isolation of the physical machine, and the latter is composed of the factors that affect the performance, energy consumption and performance–energy trade-off. For each item in this classification, we explain the features and the most relevant works.

8.1 Performance-related works

The studies related to virtualization performance aim to maximize it using virtual machine consolidation algorithms and/or monitoring and benchmarking methodologies to find the optimal features of the virtualized system to minimize the performance degradation. There is literature related to consolidation techniques and performance degradation [76,94]. In this section, we present the most relevant and current research works related to virtualization performance. All these works embrace more than one performance-influencing factor. Additionally, they are devoted to minimizing the performance degradation through virtual machine consolidation (schemes, algorithms, policies and heuristic) or to creating a performance model to predict the degradation.

The last work regarding the performance of virtual machine consolidation is performed by Selome Kostentinos and Tordsson [85]. Authors present an in-depth quantitative analysis of virtualization overheads in two groups of systems: hypervisors or containers. Also, they present the gaps of both groups on a diverse set of workloads that stress CPU, memory, storage and networking resources.

A formulation of the virtual machine consolidation problem is proposed in [82]. Moreover, Verma et al. [95] determine the effectiveness of the consolidation of virtual machines in production systems through the analysis of large enterprise workloads.

Furthermore, in [75] the authors aim to formalize a framework of the problem of dynamic virtual machine consolidation. The formalism is based on the live migration from underloaded and overloaded hosts and turning off idle nodes. The challenge is to reduce energy consumption, thus guaranteeing SLA at its highest level. The simulation results demonstrate an average reduction in energy consumption and SLA violation of 83.25% and 61.1%, respectively. Additionally, artificial intelligence [81] is used in virtual machine consolidation. In [81], the authors introduce a pseudo-Boolean-based optimization to perform optimal virtual machine consolidation. Moreover, in [8] the authors propose a technique based on machine learning interference detection. The aim is to address the virtual machine consolidation problem. The authors performed real experimentation through a web benchmark to demonstrate that the proposed approach is effective. In addition, in [50], the authors present a multi-objective optimization for the self-management of virtual machine consolidation.

In terms of virtual machine consolidation schemas, AVVMC is proposed as a consolidation scheme in [34]. AVVMC is focused on evenly distributing resource utilization. Their experiments show important benefits with respect to previous proposals, and AVVMC reduces resource wastage. In the same manner, two resource consolidation schemes with corresponding SLA constraints for MapReduce virtual machines and non-MapReduce virtual machines are proposed in [43]. The results obtained from experiments show that better performance can be achieved by collocating MapReduce and non-MapReduce jobs together in comparison with other collocating schemes. In [78], the authors propose a multi-resource selection (MRS) policy for the consolidation of virtual machines. The authors performed experiments that validate improvements in the number of physical machines and resource utilization. Additionally, a novel decentralized dynamic virtual machine consolidation schema based on an unstructured P2P network of physical machines is proposed in [32]. Extensive experiments demonstrate that their consolidation schema efficiently consolidates the virtual machines with results very close to those of a centralized system.

Moreover, in [90], the authors describe continuous virtual machine allocation and virtual machine migration. This approach enables the selection of different algorithms or policies that adapt to the impact of disturbances. In terms of clustering schemes, a correlation-aware virtual machine consolidation is proposed in [62]. The scalability problem is addressed with a two-phase clustering scheme. Using the clustering scheme, the reduction in execution time can reach 84% relative to that of one-phase solutions. The scheme also reduces the number of required physical machines and the percentage of QoS violations.

The authors in [83] define a consolidated system with a tunable bound for the performance degradation that also minimizes unused resources. The experimental results show a 52% reduction in performance degradation compared to other consolidation algorithms. In addition, in [40], the authors propose a novel QoS-aware virtual machine consolidation approach for data centres. This approach is based on historical data utilization of the CPU and the memory of virtual machines. The simulation performed with CloudSim shows improvements in QoS and energy consumption. Furthermore, in [67], a consolidation algorithm is proposed to investigate the influence of the network on typical applications in data centres. Experiments performed by the authors demonstrate improvements in the average response time of MapReduce tasks and the delay time of web applications. Dynamic consolidation of virtual machines is proposed in [16] by using adaptive heuristics. The heuristics are based on the historical data analysis from virtual machine resource utilization. The algorithm is addressed to ensure the SLA.

In a similar manner, in [73], the authors address virtual machine consolidation through the identification of overloaded physical servers from the data centre. In [9], the authors propose multi-criteria heuristics for cloud resource management by identify underutilized hosts and performing virtual machine migration. Simulations by CloudSim show up to 99% and 95% reductions in SLA violations and the number of virtual machine migrations. Additionally, in [104], several heuristics are proposed. These heuristics are based on heterogeneity aware dominant resource assistant. The authors performed a performance evaluation that validates that the proposed heuristics can achieve a consolidation performance close to that of dimension-aware heuristics.

A generic consolidation framework is proposed in [42]. The authors investigate the problem of the maximal consolidation of heterogeneous virtual machines into physical servers while protecting the SLA. Moreover, in [45], the authors propose a modular framework-based architecture. This framework combines various resource systems, a power control mechanism and virtual machine packing algorithms. The results demonstrate that virtual machines that support web applications can be consolidated and deconsolidated while simultaneously balancing the CPU load among virtual machines.

In [98], the authors propose a virtual machine consolidation algorithm for workload characteristics. The proposed algorithm is based on an approximation and dynamic programming of machines. The experiments show that the proposal obtains solutions faster than dynamic programming solutions. In a similar manner, in [47], the authors propose a consolidation algorithm to ensure the minimal the number of migrations and the maximal decision-making time. The results indicate a 60% improvement in application performance. In [11], a comparison of different virtual machine consolidation algorithms is performed in consideration of the SLA and the number of virtual machine migrations. Also, segmentation iteration correlation combination (SICC) is proposed as an algorithm for virtual machine consolidation in [105]. The authors performed numerical simulations, showing that the proposed algorithm achieves a 20% performance improvement. Additionally, a multi-objective optimization algorithm for virtual machine consolidation is proposed in [106]. The algorithm is based on biogeography-based optimization (BBO). The authors performed experiments to demonstrate that the proposed algorithm performs better than previously proposed algorithms. In addition, the proposed algorithm simultaneously reduces the power consumption and improves the load balancing.

In [56], the authors present a budget-based heuristic and multi-stage selection strategy for the problem of virtual machine allocation. Their experiments show improvements in response time, number of virtual machine migrations and communication overhead.

Cuckoo [46] is a search algorithm for virtual machine consolidation that is based on an evolutionary approach. This algorithm focuses on minimizing the resource wastage in cloud data centres. Then, a biological perspective is used in the virtual machine consolidation algorithms. Similarly, the solution proposed in [12] is based on ant colony optimization. The simulations are performed in different scenarios with random workloads. The authors observed improvements in terms of the number of virtual machine migrations, number of switch off physical machines and SLAV.

Furthermore, in [55], the authors introduce an algorithm to maximize the migration performance. The proposed algorithm has a lower time complexity than that of the existing virtual machine placement algorithms. Moreover, in [96], a migration cost estimation method is proposed; then, a consolidation score function is defined for the overall evaluation. Experiments show that IGGA performs better than existing consolidation methods. In addition, a new virtual machine consolidation algorithm is proposed in [72]. The algorithm uses a heuristic approach and migration control. Additionally, it compares the proposed heuristic with others proposed in the literature. The results show that performance of the proposed algorithm is better than that of previously proposed algorithms.

In [48], the authors propose a virtual machine consolidation policy based on monitoring techniques. The work studies the performance impact of contention in the last-level shared cache. They conclude that a strong correlation exists between the cache demand and the ratio of references for the last-level cache. In [27], the authors explore dynamic virtual machine and policy consolidation. They formulate the virtual machine consolidation problem as a policy that is shown to be NP-hard. As a result, the policy achieves benefits in terms of end-to-end delay, with a reduction of nearly 40%, and network-wide communication cost, with a reduction of 50% within a few seconds. The policy also achieves a strict satisfaction of the network policies' requirements. In [25], the authors propose a novel load detection policy. Their technique behaves better than the existing ones in terms of the number of virtual machine migrations and active host time.

In addition, a machine learning-based online placement is proposed [21]. It is a solution to the interference-aware performance that learns from an available policy trace of a large data centre owned by Google. These patterns are the ones with the lowest level of performance interference for the specified physical machine. In [74], energy efficient virtual machine consolidation policies are proposed. These policies meet SLAs. Moreover, QoS expectations are explored, and a novel SLA and energy-aware policy is proposed for dynamic virtual machine consolidation. The evaluation is performed in a cloud data centre. In addition, in [18], the authors define the problem of performance monitoring in virtual machines as the ability to extract information from the virtual machine using performance monitoring capabilities.

Performance modelling aims to develop models based on performance-influencing factors to predict the system's behaviour. In [92], the authors analyse the current modelling techniques for virtual machine performance on a data centre server and recap the research challenges.

In [51], the authors studied the interferences between the main memory and last-level cache, and consequently, they are able to estimate the interferences over an application. They define a model for interferences that can be used for virtual machine consolidation. Their results show benefits in terms of performance degradation. The authors in [54] also study the most critical elements that influence virtual machine performance and how to predict the performance degradation.

In [101], the authors attempt to find the sources of virtualization overhead. The findings indicate that the performance overhead of virtualization is acceptable for high-performance computing applications when the virtualization type is para-virtualization because of the high virtualization efficiency and the efficient inter-domain communication. Furthermore, in [4], the authors evaluate performance of virtualized servers versus non-virtualized servers in data centres. Moreover, in [57], the authors attempt to study the impact on performance of virtualization through benchmarking and monitoring techniques [71]. They measure memory usage, disc bandwidth, networking bandwidth and CPU speed (with the performance of integer and floating point operations). In [58], the authors evaluate the performance of virtualization in cloud computing and conclude that virtual machines have inherent overhead compared to physical machines. They also measure the performance of several virtual machine monitors and observe that KVM achieves the best response times.

Taking into account communications, in [61], the authors propose a virtual machine consolidation algorithm based on previous experimentation. These experiments are based on the estimation of virtual-switching-aware techniques. Real experiments using representative workloads show that the overhead represents between 10 and 30% of a servers CPU resources. Additionally, the proposed algorithm improves the SLA violation compared with the baseline algorithm.

The most important works in the field of prediction performance are presented bellow. In [59], power and performance prediction are estimated from utilization figures of the main computer subsystems, which handle the aggregated task produced by the virtualized applications. Additionally, in [108], the authors predict the QoS of the application by using an interface model. They illustrate the effectiveness of the model through a test suite and SPECweb2005. The average prediction error is less than 8%. Moreover, in [87], the authors predict the effects of interference in a cloud environment. They compare their model, MVEI, with linear and quadratic models, and the results show more precise prediction when their approach is considered. To estimate short-term CPU utilization, the authors in [93] propose a method called LRAPS that is based on the utilization history. This estimate is then used to detect overloaded and underloaded hosts as part of the live migration process. The experiments show that the method is feasible to apply and can significantly reduce power consumption and SLAV.

Taking into account the hypervisor type, some works try to study the effects of the hypervisor architecture on the system's performance. In [53], the authors show that the hypervisor has to be used for the implementation of a cloud computing system to achieve better performance. Moreover, in [65], the authors propose three optimization techniques. These techniques consider the management of the memory in the virtual machines and the handling of page faults for the access overhead of NUMA architectures. They perform real system evaluations and find a 41.1% performance improvement when consolidating 16 virtual machines.

As a collateral works, in [103], the authors propose a model of the virtual machine consolidation problem that considers different workloads. The experiment shows that the precision of the virtual machine consolidation model is high, with a 5% relative error and a 25% variance ratio. Additionally, in [102], the VITS test suite is presented. This suite can test the isolation performance of hardware and software. Experiments show that some devices can improve their weakness in the cache, memory and disc. The results also show that the Xen policy for shared resources is not fair. vExplore is a distributed virtual machine I/O performance measurement and analysis framework presented in [99].

Moreover, in [84], the proposed technique CPU utilization variance (CUV) is based on selecting the best virtual machines from over-utilized servers and migrates them into other servers to save the utilized resources and to prevent SLA violations. In addition, in [10], the authors formalize the problem of virtual machine assignment (VMA). They study four virtual machine allocation problems that depend on the capacity of the physical machine resources. To finish, it is important to analyse the performance of a single virtual machine and the performance of multiple collocated virtual machines. To perform this assessment, a methodology based on the analysis of the macro- and micro-performance is proposed in [100].

8.2 Energy-related works

Research work related to energy and power consumption aims to minimize these factors and maximize energy efficiency. There is abundant literature related to this field [5,33,49,68] that tries to achieve the stated goals mainly through consolidation and virtual machine migration algorithms. However, in this section we will show the most appropriate and current research works related to power, energy consumption and energy efficiency. To improve the power and energy consumption and the energy efficiency, algorithms based on virtual machine migration, together with frameworks, schemes, system architectures and prediction models, have been proposed.

The latest work in this field is perform in [26], which aims to study the power and energy characteristics of four main hypervisors and container engine. Authors use power measurements made over prolonged periods and workloads from CPU and main memory. The results indicate that hypervisors exhibit different power and energy characteristics.

In [28], the authors define, in a formal manner, the virtual machine consolidation problem. This definition is based on mixed integer linear programming. Additionally, they derive the necessary number of physical machines to achieve the minimum energy consumption.

Regarding the algorithms, schemes and framework, the authors in [63] propose a scheduling and consolidation algorithm (dynamic round robin, DRR) with the objective of reducing the energy consumption. In [64], the authors also propose the hybrid round robin (RR) to reduce the energy consumption when virtual machines are consolidated. This work also includes a prediction model for the power consumption of the DRR and the hybrid RR algorithms. The results show benefits of 56.4% and 55.9% of power reductions for DRR and hybrid RR algorithms, respectively.

In [37], the authors propose an approach to virtual machine consolidation to improve the energy consumption of storage and virtual machine migrations. The proposed approach is implemented using the Eucalyptus framework and demonstrates several energy savings. In [24], there are two main contributions. The first is the establishment of a decision algorithm based on SLAV to determine whether a host is overloaded. The second is a policy to minimize power consumption and maximize resource utilization. The proposed algorithms guarantee a decrease in energy consumption between 21 and 34%, a decrease in energy–performance metric between 87 and 94% and a 63% reduction in execution time. Moreover, in [77], the authors present a virtual machine consolidation algorithm based on resource utilization prediction to improve the energy efficiency of cloud data centres. The results show that the proposed consolidation algorithm reduces the number of migrations and the power consumption. Moreover, the SLA is not violated, in contrast to previously proposed methods.

Moreover, in [97], the authors propose a virtual machine consolidation algorithm to improve the virtual machine placement and to reduce the energy consumption. The proposed algorithm behaves better than the first fit decreasing algorithm, saving up to 25% more energy. In addition, in [23], the trade-off between SLA violations and host overload is studied. The authors propose a framework that achieves a 27% decrease in energy consumption, 78.4% fewer SLA violations and an 84.1% decrease in the energy–SLA violation ratio.

The authors of [88] propose two virtual machine packing algorithms (MBA and greedy). A reduction in total power consumption of between 18 and 50% is observed. In addition, in [6], the authors propose a virtual machine consolidation framework that reduces the energy consumption while guaranteeing the QoS. The simulation results, with CloudSim, show improvements in energy consumption and SLA violations. Moreover, in [89], an approach is proposed that consists of three algorithms: over-utilized host detection, virtual machine selection and virtual machine placement. The experimental results show improvements in the number of power changes, number of migrations and SLA violations. Moreover, the energy consumption and the number of virtual machine migrations are decreased. Additionally, a heuristic based on the resource allocation of virtual machine selection is proposed in [39]. This heuristic addresses the problems of energy consumption and operational cost reduction while preventing SLA violations. The authors' experiments validate the approach and show an increase in the cloud providers profit and energy savings.

Another virtual machine consolidation algorithm that minimizes the active physical servers and reduces the energy costs is proposed in [31]. The authors perform trace-driven simulations to demonstrate that the performance is not affected and that the energy consumption is reduced. To finish, PVDE is an energy efficient algorithm presented in [107] for the consolidation of virtual machines. This algorithm reduces the energy consumption and maintains a suitable level of SLA violations.

Regarding the system architecture and infrastructure, the authors in [30] propose a consolidation of virtual machines by accounting for the network and data centre infrastructure and, consequently, reduce the number of employed racks and routers. They reduce the energy consumption by 2.5% in the physical machines and by 18.8% in the communication systems. Furthermore, in [7], how to create resource usage profiles in terms of energy consumption is studied. Moreover, in [91], the authors propose two processes with consolidation in batch mode for reserved virtual machines and an online placement for on-demand virtual machines. They use a Hadoop testbed for the experiments, which show energy savings.

In addition, in [29], the authors consolidate a set of virtual machines on a physical machine to improve the resource utilization. In the consolidation process, they consider the cooling and communication structure of the data centre. The authors execute four benchmarks in real data centres, and they observe improvements in the energy consumption of the data centres network equipment and cooling.

The authors in [37] define a related multi-resource utilization methodology using a double threshold. The aim is to trigger the migration of virtual machines and to reduce the number of active physical machines and the amount of virtual machine migrations. The data centre shows better energy efficiency when implementing this method. In addition, in [20], the authors propose a methodology based on the dynamic execution time, power and energy measurement to build a prediction model. The authors also conclude that it is more difficult to maintain the parallelized implementation.

To finish, in [36], the authors propose a prediction method to improve the energy efficiency in the virtual machine consolidation process, as well as the QoS and performance. Furthermore, in [109], the authors propose a novel approach to improve the energy efficiency in consolidated environments by applying robust optimization theory. They perform a numerical evaluation and show that the proposed model enables the cloud provider to balance the power consumption and the SLA.

8.3 Performance–energy trade-off works

The performance–energy trade-off is a field that has been studied to a lesser extent in recent years. No existing literature summarizes the main contributions. Therefore, we present the most relevant contributions to this field.

In [66], the authors demonstrate that the allocation of virtualized services in a heterogeneous server infrastructure is NP-hard. The energy optimal allocation problem can be modelled as a variant of the multidimensional vector packing problem. Additionally, they propose a performance prediction model for service degradation when services are consolidated. The proposed prediction model considers the trade-off between power consumption and service performance.

A remaining utilization-aware (RUA) algorithm for virtual machine placement and a power-aware algorithm (PA) are proposed in [63]. The algorithm determined the appropriate physical machines to shut down to obtain a greater improvements in terms of energy saved. The authors demonstrate, through the use of simulations, a trade-off between energy consumption and SLA violations. The first algorithm, RUA, is also useful for the case of variable workloads because it avoids overloading virtual machines in the same physical machines and, consequently, reduces SLA violations. In addition, in [22], the authors propose a dynamic allocation and selection policy for virtualized data centres to reduce energy consumption and SLA violations.

Regarding virtual machine consolidation approaches, in [69], the authors propose a cooperative learning technique based on multi-agents to address the virtual machine consolidation challenge. The results indicate a better energy–performance trade-off in cloud data centres in comparison with that of SOA algorithms.

In order to measure the goodness of the virtual machine consolidation, [15] proposed a new index, namely CiS^2, which quantifies the relation of performance degradation and energy efficiency under parallel workload execution, that is, the trade-off of performance and energy in consolidated environments. This index help performance engineers to decide about the suitability of a consolidation degree.

9 Discussion

The aim of this section is to analyse the results obtained from the research works on classification considered in Table 2.

Many papers have focused on studying the data centre as a whole rather than a single physical server. This occurs independently of research field, that is, performance or energy, because the current cloud computing services are supported by virtualization technology.

However, the factors that have been less studied are the virtualization overhead and the interference between virtual machines. This fact is due to the difficulty in isolating the physical hardware from the software services that are hosted in the hardware. By contrast, the factors that have been more thoroughly studied are the performance as a function of the physical machine resource utilization, the workload type and the SLA. These factors are directly related to the services offered by the infrastructure providers. These topics may be popular because physical machine resources can be

Table 2 Proposed categorization taking into account performance, energy and trade-off-influencing factors

	Data centre	Single server
Performance		
VMM type		
HW type	[5,58,101,102]	[53,57]
OS type	[4]	[57,99]
VM interference	[8,87,102,108]	[51,99]
VM features		
Number of vCPUs	[6,7,9,22,23,32,40,42,55,58,78,81, 91,102]	[57,99,103]
Amount of vRAM	[6,9,22,23,40,58,78,81,96]	[57,99]
VM resource utilization		
%vCPU	[6,16,34,38,42,45,46,77,87,91,92,96]	[48,54,103]
%vRAM	[6,16,92,96]	[48,103]
PM resource utilization		
%CPU	[4–6,8,12,21,22,25,28,29,31,32,34, 36,38–40,42,45,46,55,56,60,61,72, 74,75,77,78,83,84,87,89,90,93,97, 107,109] [85]	[10,24,54,62,62,99]
%RAM	[5,6,21,39,40,84,87,97]	[99]
PM features	[7,9,12,20,21,23,28,30,39,40,45,50, 58,62,66,72,74,82,88,91,93,96,104, 106]	[10,18,54,57,59,65]
Workload type		
RAM	[21,40,96]	[18,59]
CPU	[4,8,9,20,21,25,27,29,31,32,36,37, 39,40,43,50,55,58,61,63,67,69,74, 75,78,81–84,88,90– 92,100,101,104,106–108]	[48,53,54,59,95,98,99]
Network	[4,20,21,31,43,101]	[95,98]
HD	[47]	[48,95]
Overhead	[38,85]	[95]
SLA	[56,61,101,104]	[18,54,65]
Number of VMs per PM	[6,9,11,12,16,22,23,25,27,30,38– 40,42,61,62,69,72,74,75,77,84,89, 93,97,107,108]	[24,62]
Energy		
Energy consumption	[6,9,12,16,20,22,23,25,28–31,34,36– 38,40,55,56,60,66,72,75,83,84,89, 91,97,106,107]	[24]
Energy efficiency/awareness	[11,60,63,64,74]	[10,26,98]
Power consumption	[6,7,11,20,22,39,46,50,63,64,72,77, 88,89,93,106,109] [85]	[10,24,59]
Energy–performance trade-off	[6,15,38,66,69]	[15,24]

monitored directly, and the workload type and the SLA can be studied independently of the physical infrastructure. Therefore, the factors depend on the customer features and the response time of the system as a whole.

Regarding the energy consumption, the fewest studies are related to power consumption and energy efficiency. The former can be inferred by the direct relation between the power consumption and the physical features of the devices and the technological dependency. The latter is due to the difficulty of changing the energy consumption linearly with the workload. Specifically, in consolidated physical servers, the energy consumption is less predictable.

We observe a reduction in the number of studies related to the performance–energy trade-off possibly because of the lack of techniques and metrics to quantify the trade-off. As stated previously, the number of studies related to isolated servers is less than the number related to data centres. In terms of the performance of a single server, the most studied factors are the physical machine resource utilization and the workload type. This is due to the ease of measuring the resource utilization of a physical server and the malleability of the workload features in single servers. However, the factors that have a lack of research are the virtualization overhead and the virtual machines interference, as in the data centre case. In the same manner, there is difficulty in isolating the services from the hardware, and there is a lack of methodology for studying the overhead and the interferences caused by virtualization.

Furthermore, there is a lack in research on energy consumption and energy efficiency due to the difficulty of predicting the response time of consolidated servers. Additionally, the energy–performance trade-off is less studied, as in the case of data centres.

To conclude, we observe a lack in research in some fields. For both data centres and single servers, there is a need to develop research focused on improving the performance of the system, taking into account the virtual machine monitor type and the model and analysis of the virtualization overhead and virtual machines interference. In addition, there is a lack of research on energy efficiency and the performance–energy trade-off.

The performance and energy and the trade-off of consolidated systems must be understood to improve them and take advantage of virtual machine consolidation. Therefore, a huge opportunity to study and develop research works in these fields exists.

10 Conclusions and future work

In this paper, we have summarized the past ten years of research related to the performance–energy trade-off of consolidated virtualized systems. Additionally, we have reviewed the main concepts related to virtual machine consolidation as a technique for greening data centres and reducing their energy and power consumption. Moreover, we have presented the concept of energy efficiency and energy proportionality to improve energy predictability for green virtualization and consolidation techniques. We have studied the factors that influence the performance degradation of virtualized systems, as well as the energy-influencing factors. We have included the energy–performance trade-off in our research work categorization.

The main contribution of this paper is the categorization of the related literature in these three main factor classes. From these classes, we have reviewed the aim of each paper and its principal contribution. The resulting subclasses arise from the main topics in the systematic literature (see Table 2). We conclude that the research community has not fully studied some fields, such as virtualization overhead, virtual machine interference, energy efficiency and energy–performance trade-off, in contrast to some more thoroughly studied fields, as shown in Table 2.

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