Software-Driven Strategies to Reduce the Energy Footprint of Data Centers: A Systematic Literature Review

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ABSTRACT

Internet traffic and data usage continue to increase over time. Consequently, the energy footprint of the ICT sector grows exponentially and significantly contributes to the global greenhouse gas emissions (GHGEs). Data Centers (DCs) have with 45% the largest energy footprint within the ICT sector. Hence, there is a need to reduce the energy footprint of DCs. In this study, we are interested in providing an overview of software-driven strategies to reduce the energy footprint of the ICT equipment of DCs. To this end, we conduct a Systematic Literature Review (SLR) in which we selected and analyzed 224 primary studies published in 2018-2021. The insights from this study are useful for researchers to understand which strategies are well-studied and which gaps remain. Furthermore, practitioners can utilize the overview as a guideline to adapt the strategies in practice. We identified five main strategies, namely: VM consolidation, Resource management, Monitoring, Network optimization, and Container consolidation. Furthermore, we identified characteristics, such as metrics, algorithms, and evaluation types, from these strategies and used this to compare the various strategies.

KEYWORDS

Systematic Literature Review, Energy, Strategy, Software, Data Center, ICT equipment

1 INTRODUCTION

Internet traffic and data usage continue to increase over time. In 2020, nearly 60% of the global population is estimated to be an active internet user. This is an increase of 7% compared to the previous year [17]. This rise is amplified by Internet of Things (IoT) technologies and the 5G network [30]. Furthermore, the rapid swift to remote work due to the COVID-19 pandemic caused a significant increase in data traffic [20]. The energy footprint of the Information and Communication Technology (ICT) sector grows exponentially and significantly contributes to the global greenhouse gas emissions (GHGEs). Belkhir et al. [3] predict that the global GHGEs of the ICT sector relative to the worldwide footprint doubles from 1-1.6% in 2007 to 3–3.6% by 2020. As means of comparison, in 2018, the energy footprint of the aviation industry accounts for around 2% of the global GHGEs [15]. Data Centers (DCs) have with 45% the largest energy footprint within the ICT sector [3]. The amount of energy currently consumed by DCs is unsustainable [22]. This stresses the need to reduce the energy footprint of DCs.

Several solutions are proposed in the literature to reduce the energy footprint of DCs. For instance, DCs adopt renewable energy sources to cut their power costs and reduce their environmental impact. A drawback of using renewable energy sources is inconsistent availability [19]. Furthermore, the energy consumption of DCs can be reduced by switching off idle servers. The resource utilization of severs is between 10% and 50%, hence, causing many servers to be idle. Idle servers consume up to 50% of the power compared to full utilization while not contributing to the operation. Server utilization can be improved by virtualization and consolidation techniques [33]. Last, cooling the ICT equipment consumes a significant part (roughly 38%) of the energy in DCs. This energy can be reduced through thermal management and cooling strategies [24]. Unfortunately, none of these solutions by themselves are expected to be sufficient to radically reduce the energy footprint of DCs and create a sustainable situation [22].

In this study, we are interested in software-driven strategies to reduce the energy footprint of DCs. We chose to focus on software-driven strategies compared to hardware-driven strategies as software optimization is deemed more promising compared to hardware optimization. To illustrate, optimal energy efficiency can not be achieved using ideal hardware as energy consumption is not only limited to the efficiency of physical resources [16]. Furthermore, we focus on the energy consumption of ICT equipment compared to electrical and supporting equipment as ICT equipment accounts for the largest proportion of energy usage within the DC [31]. Moreover, thermal and cooling strategies, which account for the second-largest part of energy usage, are already well-studied and adapted [21, 24, 31].

In our study, we conduct a Systematic Literature Review (SLR) to identify state-of-the-art software-driven strategies to reduce the energy footprint in DCs. This is useful for researchers to understand which strategies are well-studied and which gaps remain. Furthermore, practitioners can utilize the overview as a guideline to adapt the strategies in practice.

The remainder of the paper is structured as follows. First, Section 2 presents related work and Section 3 provides background information on the energy footprint of DCs. Next, Section 4 describes the

*This author has a leading contribution in structuring and conducting the research, defining the project scope and design, and writing the report.
†These authors contributed by selecting the primary studies, extracting and labeling the data, and identifying the categories and labels.

study design of the SLR. Afterward, Section 5 presents the results and Section 6 discusses the results. Last, Section 7 reflects on the potential threats to validity and Section 8 concludes the study.

2 RELATED WORK

This section discusses studies that performed a similar SLR in related domains. Many studies review academic literature on strategies to save energy in DCs. Most studies focus on a particular part of the DC (e.g., network, cooling equipment) or a certain software strategy (e.g., VM placement, consolidation).

First, we discuss the work of Procaccianti et al. [27]. The authors performed a SLR review on energy efficiency in cloud software architectures. Cloud computing is an example of a technology that has the ability to reduce the energy consumption of ICTs by improving hardware utilization. Procaccianti et al. identified three strategies to reduce energy consumption in software architectures, namely: *Energy Monitoring*, *Self-Adaptation*, and *Cloud Federation*. Self-Adaptation (i.e., adapting software behavior to increase energy efficiency) was most frequently observed as a strategy to increase energy efficiency. Related is the work of Vasques et al. [34], who conducted a review on energy efficiency and demand response focusing on small and medium DCs.

The next study that we discuss is conducted by Moghaddam et al. [23]. They presents a SLR on energy-efficient networking solutions in cloud-based environments. The authors identified the following strategies to increase the energy-efficiency through networking: *Sleeping mode/Swithiching off*, *Traffic consolidation*, *VM consolidation*, *Optical devices*, *Energy-aware routes*, *Traffic patterns*, *Traffic locality*, *Energy-aware devices*, *Heat minimization*, *Traffic minimization*, and *Green energy*. Sleeping mode/Switching off (i.e., deactivating idle network devices), Traffic consolidation (i.e., aggregate network traffic into fewer numbers of links and devices), and VM consolidation (i.e., aggregate VMs into fewer numbers of physical machines) are observed to be the most frequently addressed strategies. Another study focusing on the network is performed by Chang et al. [4]. The authors reviewed key technologies for saving energy in DC networks. The key technologies that they identified are: *network topology optimization*, *network routing optimization*, *flow scheduling*, and *intelligent electric management and optimization*.

The work of Kong et al. [19] focuses on the renewable energy-aware power management problem of DCs. The authors conducted a survey to classify studies that consider renewable energy and/or carbon emissions. Furthermore, Liu et al. [21] focus on cooling systems integrated with Thermal Energy Storage (TES). They presented an overview of research and applications of TES technologies in DCs that aim to save energy. Related work is conducted by Nadjahi et al. [24] who present a review on energy-saving thermal management and cooling technologies in DCs.

Dayarathna et al. [6] performed a survey around DC energy consumption modeling. They surveyed state-of-the-art techniques to model the energy consumption of DCs and their components. They focused both on hardware- and software-centric power models. The hardware-centric approaches consider low-level models (e.g., circuit-level) and high-level models (e.g., sever or DC level). Software-centric models focus on the OS, VMs, or applications.

Khan et al. [18] conducted a literature review on energy-efficient software techniques and their impact on the QoS and SLA-violations. The authors conclude that *workload scheduling* is the most frequently adopted technique. They stress the need to develop a standardized set of performance measures to benchmark software techniques for energy-efficiency in cloud DCs.

Dhanoa [7] performed a review on energy-efficient optimization techniques for VM placement in cloud DCs. The author focused on evolutionary algorithms (e.g., Genetic Algorithm, Ant Colony Optimization, and Particle Swarm Optimization) which can be applied to reduce the energy consumption of servers during the VM placement step of the VM consolidation process. Similarly, Prahba et al. [26] conducted a review on dynamic VM consolidation approaches for energy-efficient cloud DCs. The work of Usman et al. [32] is related as well as they conducted a literature review on energy-efficient nature-inspired techniques in cloud computing DCs.

Our study is distinct as we aim to capture all software-related strategies that apply to the ICT-equipment of the DC. This is a relatively generic scope, hence, we adopt a relatively broad search query (Section 4) in contrast to more restrictive queries such as in the work of Khan et al. [18]. Moreover, many related studies specifically focus on cloud DCs. In contrast, we adopt a broader scope by including all DCs. Last, our work includes many strategies (e.g., models, metrics, algorithms) that are not restricted by a specific type of algorithm or technique. The main contribution of this work is an overview of the distribution of state-of-the-art software-driven strategies to reduce the energy footprint in DCs.

3 BACKGROUND

This section discusses background information regarding the energy footprint in the context of DCs. DCs consume a significant amount of energy [3]. The main motives to reduce the energy footprint in DCs are to reduce the GHGEs and energy costs [19]. Section 3.1 defines the concept energy footprint and Section 3.2 presents common metrics to monitor the energy footprint of DCs. Last, Section 3.3 describes the high-level components of DCs together with common strategies to reduce the energy footprint of these components.

3.1 Reduce energy footprint

Energy is measured in Joules and can be expressed as power (Watt) over time (seconds). Therefore, energy can also be expressed in kilowatt/hour (kWh) [8]. In the literature, several similar but distinct concepts are used to discuss the energy footprint of DCs. In this section, we aim to disambiguate these concepts. We start by defining and explaining the difference between energy efficiency and energy consumption (Section 3.1.1). Afterward, we elaborate on renewable energy usage (Section 3.1.2). Last, we describe our interpretation of the energy footprint as adopted in our SLR (Section 3.1.3).

3.1.1 Energy efficiency and energy consumption. Perez-Lombard et al. [25] defined and analyzed energy efficiency as well as related concepts. *Energy consumption* can be defined as “the service demand times the energy intensity". *Energy intensity* is “the amount of energy needed to provide the unit of service or activity". In other words, energy consumption is the absolute energy used by a service or activity. This relates to *energy-saving* which is defined as "a reduction in the use of energy". Hence, energy-saving means reducing the energy consumption. On the other hand, *energy efficiency* is commonly used to indicate technological improvements to reduce the energy intensity. Energy efficiency can be defined as "the ratio between service output or results and the energy input required to provide it". Hence, energy efficiency involves a relation to the service output. This means that the energy efficiency can increase by increasing the service output using the same amount of energy. Thus, increased energy efficiency does not automatically imply that the energy consumption is reduced. An increase of the energy efficiency *could* lead to energy-savings and energy-savings *could* lead to increased energy efficiency. Perez-Lombard et al. [25] stress that energy efficiency strategies are not sufficient to address global energy challenges. They state that the amount of energy consumed by systems should be reduced to mitigate the impact on the environment.

3.1.2 Renewable energy. Currently, DCs most frequently utilize fossil-based fuels as main energy source as these fuels can continuously generate electricity. Unfortunately, fossil-based fuels are exhaustive and a primary source of GHGEs. To reduce the negative effects on the environment, exhaustible (brown) energy sources can be replaced by renewable (green) energy sources such as wind and solar power. A downside of using renewable energy sources in DCs is the uncertain availability due to weather conditions [19]. Strictly speaking, replacing brown energy with green energy does not affect the energy efficiency and consumption as the amount of energy used remains constant. However, it does reduce the environmental impact [25].

3.1.3 Energy footprint. In this study, we are interested in identifying strategies to reduce the negative effects of the energy usage of DCs. As explained in the previous two sub-sections, reducing the energy footprint involves reducing the absolute energy consumption, increasing the energy efficiency, and optimizing the use of renewable energy. Strategies to reduce the energy costs without actually reducing the energy footprint are out of scope as these do not directly contribute to mitigating the negative effects of the energy footprint on the environment.

3.2 Monitor energy footprint

The most well-adopted metric in practise to measure the energy efficiency of DCs is the Power Usage Effectiveness (PUE). The PUE represent the ratio of the power used by the complete DC to the energy used of the ICT-equipment [13]:

$$PUE = \frac{total\ facility\ power}{ICT\ equipment\ power}$$

The PUE has been criticized as it is an incomplete metric for capturing the energy footprint of DCs. It is certainly useful to understand the energy overhead of the facility, however, the metric does not measure the energy-efficiency of the computing hardware, the energy productivity, or the energy performance regarding the carbon emissions [13].

Many other metrics and KPIs are available. For the interested reader, we refer to the work of Reddy et al. [28]. In this work, the authors provide a thorough overview and classification of metrics that measure different DC components. An interesting approach to monitoring the sustainability of DCs is presented by Lykou et al. [22]. The authors introduce a novel sustainability scoring model that combines the evaluation of the environmental impact and operational efficiency of DCs.

3.3 Data center

According to CISCO [5], a DC can be defined as a "physical facility that organizations use to house their critical applications and data". This involves multiple ICT resources that are connected through a network. Nowadays, modern DCs frequently adopt a level of virtualization on top of the physical infrastructure. The three main components of a DC are ICT equipment (Section 3.3.1), supporting equipment (Section 3.3.2), and electrical equipment (Section 3.3.3).

3.3.1 ICT equipment. The ICT equipment of a DC consists of computing resources, storage devices, and network equipment. The main elements of a server are the CPU and memory (e.g., RAM). Servers are organized into racks together with storage equipment (e.g., disks) and the network infrastructure (cables and switches). The network establishes the connection between the local (virtual and physical) servers as well as the connection between the DC and the users or remote servers. In the DC, the servers consume relatively most of the energy. Servers can store, analyze, and transmit large amounts of data. Unfortunately, idle servers still consume up to 50% of the power of a fully utilized server without contributing to the operation. This results in servers often being underutilized [33]. Most modern DCs add a layer of virtualization comprising of VMs and/or containers. These virtualized components can be consolidated onto PMs to utilize the resources more efficiently. As a consequence, idle servers can be switched off to save energy. Many algorithms exist of distribute VMs over PMs [7, 18, 26, 32].

3.3.2 Supporting equipment. A significant proportion (approximately 38%) of the energy consumed by DCs results from supporting infrastructure [24]. Assembling various IT equipment in a building generates heat. This should be removed by cooling techniques. Examples of cooling techniques are: air-cooled systems, water-cooled systems, and two-phase cooled systems [14]. Thermal management is both required at device- and system-level. Device-level energy management involve preventing the elements from overheating. System-level strategies involves temperature-aware distribution of the workload among devices [11]. Other supporting equipment, such as lightning, have a negligible effect on the overall energy usage of DCs [24].

3.3.3 Electrical Equipment. Barroso et al. [2] describe a simplified design of the DC power systems. In a typical DC, the power enters the facility through an outside transformer located in a substation of the DC. The power flows to the Uninterruptible Power Supply (UPS) which typically combines the following tasks: (1) chose and switch to optimal power input, (2) provide battery power to bridge the time between a possible power failure and available generator power, (3) conditioning the incoming power flow (e.g., removing voltage spikes). UPS batteries are considerably large, hence, therefore usually placed in a separate room. Finally, the output of the UPS is routed to PDUs near the ICT equipment.

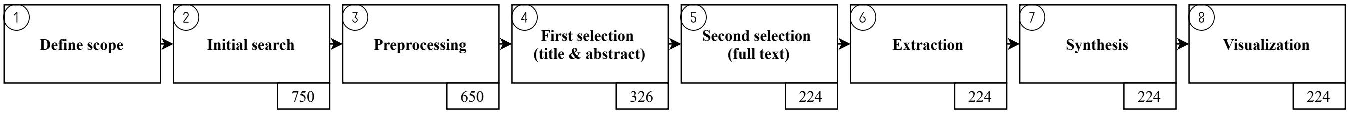

Figure 1: Overview of the research steps (① - ⑧) and the number of studies that remain after conducting each step (▭).

4 STUDY DESIGN

In this study, we conduct a SLR by following the protocol described by [9]. The study design is visualized in figure 1. In this figure, steps (① - ⑧) represent the various phases of the study. The number in the rectangle (▭) attached to each step represents the number of studies that remain after conducting the step. In step ①, we define goal and research question (Section 4.1). In step ②, we define the search strategy and the query to obtain the initial studies (Section 4.2). In step ③, we preprocess the data retrieved in the initial search (Section 4.3). In steps ④ and ⑤, we select the primary studies based on inclusion and exclusion criteria (Section 4.4). In steps ⑥ and ⑦, we respectively perform the data extraction (Section 4.5) and synthesis (4.6) process to extract information from the primary studies. Last, in step ⑧, we visualize and analyze the results (Section 4.7). All the intermediate steps are traceable and available in the replication package (Section 4.8).

4.1 Scope

This section presents the goal and research question of our study. The **Goal (G)** is: *To provide an overview of the state-of-the-art software-driven strategies aimed at reducing the energy footprint of DCs.* The **Research Question (RQ)** is: *What are the state-of-the-art software-driven strategies aimed at reducing the energy footprint of DCs?* The concepts *energy footprint* and *data center* are defined in Section 3. We do not define the concepts *software-driven* and *strategy* prior to the study as we aim to extract the definitions from the reviewed studies. Relevant strategies include methods to reduce, monitor, or predict the energy footprint. Last, *state-of-art* refers to the recent publication years of the selected studies.

4.2 Initial search

To answer **RQ**, we formulate and execute a search query to retrieve relevant studies. The search is executed in *Google Scholar*[1] as this is currently the largest database of scientific literature. Furthermore, Google Scholar is easily accessible to other researchers which improves the replicability of the study. To perform the search, we selected keywords based on **RQ**. The keywords are: *software-driven*, *strategy*, *energy footprint*, and *data center*. To include all relevant literature, we need to consider synonyms and related terms as well. We chose to omit the keywords *software-driven* and *strategy* from the search query as these terms were too restrictive. Moreover, we generalized the keyword *energy footprint* to *energy* to ensure that all relevant studies are included. During the initial search, it is essential to obtain high recall as all studies are retrieved in this stage. Afterward, during the selection phase, relevant studies are selected. The keywords resulted in the following **Search Query (SQ)**:

```
allintitle: energy ("data center" OR "data centers" OR
datacenter OR datacenters)
```

We specified that the keywords need to be present in the title of the research papers to reduce the amount of noise and create a literature base that is feasible to manually inspect. To ensure that we target state-of-the-art strategies, we only considered studies that are published between 2018 – 2021. Furthermore, the demarcated range of publication years ensures the feasibility of the study. Executing this search query on the 12th of January 2021 resulted in a total of 750 hits. We utilized *Publish or Perish*[2] to execute the search query in Google Scholar and retrieve a list of citations and meta-data of the studies in `csv` format.

4.3 Preprocessing

We applied a couple of preprocessing steps to the search results prior to manually inspecting the retrieved studies. First, we randomized the order of the articles using Google Sheet's built-in functionality `randomize range` to prevent an effect of the ranking from Google Scholar on the results of our study. Afterward, we removed search results that consist of an empty citation (i.e., the search result does not link to an actual article) using a script in Google Sheets. Last, we removed search results that link to Google Patents as these are non-scientific articles that are not peer-reviewed. The applied scripts are available in the replication package (Section 4.8). After preprocessing, 650 selected studies remain.

4.4 Selection criteria

To select *primary studies* (relevant studies selected for analysis), we defined **Inclusion Criteria (ICs)** and **Exclusion Criteria (ECs)**. These criteria are based on the relevance with respect to the **RQ** and the scientific validity and quality of the studies. Studies are a primary study if they meet all the **ICs** and none of the **ECs**.

The **ICs** are:

- **IC1** *The study introduces at least one strategy to reduce, monitor, or predict the energy footprint.* This IC is utilized to select only studies that contribute concrete strategies to mitigate the negative consequences of the energy usage of DCs.
- **IC2** *The strategy is software-driven.* This IC specifies the focus on studies that introduce strategies that can be implemented through software. An example of an software-driven strategy is a task scheduling algorithm.
- **IC3** *The strategy applies to ICT equipment.* This IC emphasizes the focus on the measurement and optimization of the ICT equipment in the DCs. Examples of ICT equipment are: network, storage, server, CPU, and memory.

[1] https://scholar.google.com

[2] Harzing, A.W. (2007) Publish or Perish, available from https://harzing.com/resources/publish-or-perish

Header	Description
`ID`	Each study has a unique numeric identifier.
`Title`	The full title of the study.
`URL`	URL to the study as retrieved by executing **SQ** in Google Scholar.
`Authors`	The full list of authors of the study.
`Venue`	The full name of the venue of the study.
`Venue Acronym`	The acronym of the name of the venue of the study.
`Venue Type`	The venue type of the study. Considered venues are Journal (`J`), Conference (`C`), or Workshop (`W`).
`Year`	The year in which the study is published.
`Selection Criteria`	For each selection criterion (**IC1** - **IC5** & **EC1** - **EC9**), a separate column tracks whether the article meets this criterion. If the criterion is met, a `1` is inserted, otherwise, a `0` is inserted.
`Primary Study`	This column tracks whether the study is selected as a primary study. If the study is selected, `Yes` is inserted, otherwise, `No` is inserted.
`Selected based on title & abstract`	This column tracks whether the study is selected based on the title and abstract. If the study is selected, `Yes` is inserted, otherwise, `No` is inserted.
`Reviewer`	This column records the initial of the researcher who reviewed the study.
`Notes`	This column is utilized to insert any remaining notes.

Table 1: Recorded data points for each study retrieved in the initial search.

IC4 *The study evaluates the introduced strategy.* This IC ensures the correctness of the selected strategies.

IC5 *The study focuses on DCs.* This IC is introduced to specify that the main focus of the relevant studies are DCs as defined in Section 3.3. This includes (but is not limited to) cloud DCs.

The **ECs** are:

EC1 *The study focuses on optimizing the hardware of ICT equipment or the physical environment.* This EC emphasizes the focus on software-driven strategies, hence, all optimizations related to the hardware or physical infrastructure (e.g., racks, building architecture) are out of scope.

EC2 *The study focuses on the energy footprint of supporting equipment such as lightning, cooling, and thermal management.* This EC excludes all strategies that do not focus on the ICT equipment. For example, strategies focusing on UPS or cooling fans are out of scope.

EC3 *The study focuses on energy generation, transformation, or supply technologies.* This EC is introduced to exclude all strategies that consider energy-specific optimization strategies as our study is conducted from a computer science perspective.

EC4 *The study is not written in English.* This EC is adopted as English is a main language for scientific literature and English literature can be adequately assessed by the authors.

EC5 *The study is not peer-reviewed.* This EC is utilized to guarantee the quality of the studies under review and, therefore, the quality of the review itself.

EC6 *The study is a secondary or tertiary research such as a SLR or survey.* In this research, we are interested in providing an overview of strategies to reduce the energy footprint, studies that provide an overview of existing strategies do not adhere to this requirement and including them would lead to duplicates. Secondary and tertiary works are discussed in Section 2 (Related Work).

EC7 *The study is in the form of a poster, presentation, tutorial, thesis, or book.* These studies either do not provide the necessary detail or are too detailed and, therefore, not feasible to manually inspect.

EC8 *The study is a duplicate or extension of another study within the review.* This EC ensures that certain topics are not overrepresented in the review. When extensions of relevant studies are encountered, the studies are clustered and the most encompassing study is chosen for review.

EC9 *The study is unavailable.* Studies that are not available cannot be analyzed by the researchers.

The **ICs** and **ECs** are assessed in two iterations. In the first iteration, we selected studies based on the title and abstract. This resulted in a total of 326 selected studies. In the second iteration, we read the full articles of the selected studies and assessed whether these are primary studies. We identified a total of 224 primary studies. For each study, we record the data as specified in Table 1.

4.5 Extraction

In this section, we present the used method to extract the data from the primary studies. The objective of the data extraction step is to collect the relevant data from each study in order to accurately compare the studies. This step is performed by three authors of the study who frequently met to ensure a uniform procedure. In the data extraction step, the full article of each primary study is read. Afterward, the relevant data is recorded in a well-structured spreadsheet. This spreadsheet has 9 columns in which the data is recorded according to the categories specified in Table 2. These categories are defined based on the **RQ**, **ICs**, and **ECs**.

Category	Description	Possible labels
Energy related goal	This category specifies the objective of the study towards energy.	`Reduce energy`, `Increase EE`, `Renewable`, `Monitor`, `Reduce costs`
Strategy type	This category presents a high-level description of the strategy to reduce the energy footprint.	`Resource`, `VM consolidation` , `VM selection`, `VM migration`, `VM placement`, `Predict`, `Measure`, `Model`, `Network`, `Container`
Algorithms/Techniques	This category lists algorithms and techniques used to realize the strategy.	`Nature`, `ML`, `GP`, `LP`, `DVFS`, `Fuzzy`, `Fit`
Software-driven	This category describes the relation between the strategy and software.	`Completely`, `Partly`, `Depends`
Energy related metrics	This category lists the used metrics to assess the energy-related performance of the strategy.	`Energy consumption`, `Power consumption`, `Energy efficiency`, `Energy & SLA`, `Renewable`, `Supporting & ICT`
Other metrics	This category lists the used metrics to assess the performance of the strategy in dimensions that are not energy-related.	`VM`, `PM`, `SLA`, `Resource`, `Time`, `Workload`, `Cost`, `Network`, `Algorithm`, `Footprint`, `Supporting`
Evaluation	This category describes the used evaluation to assess the strategy.	`Simulated`, `Empirical`, `Theoretical`
Data center component	This category describes the hardware components of the DC to which the strategy applies.	`DC`, `Server`, `CPU`, `Memory`, `Network`, `Storage`
Data center type	This category lists the type or specific requirements of the DC that is considered in the study.	`Cloud`, `Heterogeneous`, `Homogeneous`, `Geo-distributed`, `Renewable`, `Virtual`, `Large`, `Medium`, `Small`

Table 2: Categories of extracted data and possible labels to synthesize the data.

4.6 Synthesis

After the data extraction, we defined labels within each category that capture the possible information types to represent the extracted data from the studies. We defined these labels using a group discussion in which we classified the most frequent labels encountered during the extraction. Moreover, we constructed diagrams in which the relation between the several labels is expressed. This supported us in choosing the appropriate level of abstraction and relevance of the labels. The labels of each category are listed in Table 2. Moreover, a complete list of the definitions and example date for each label is presented in Appendix A.

To ensure consistency, three researchers labeled a small selection of the same studies. This selection included studies extracted by each researcher. We compared whether we chose the same labels to ensure that we are working according to the same procedure and agree on the definition of each label.

If the extracted data describes a concept that can not be captured by one of the pre-defined labels, we utilized the label `Other`. We created a spreadsheet in which we kept track of the extracted data that is classified in the Other category. This spreadsheet is used to dynamically derive more labels. As a rule of thumb, when a concept is mentioned less frequently than 5 times, we classified it as Other. If the concept occurred more frequently, a new label emerged. When no relevant data can be extracted from the study, the particular cell remained empty. Hence, all the Other labels correspond to an actual concept for which no relevant label exists.

4.7 Visualization

Last, we plotted and analyzed the derived labels for each primary study using `Jupyter Notebooks`[3], `Python 3`[4], and the packages: `Pandas`[5], `Matplotlib`[6], and `Seaborn`[7]. The results are presented and discussed in Section 5.

4.8 Replication package

To ensure replicability and independent verification of the study, the complete research protocol is described in Section 4. Furthermore, a replication package is publicly available on https://github.com/sophie-vos/SLR. This repository contains: (1) the search output of the initial search and code to perform the preprocessing, (2) the spreadsheet containing the data from the selection, extraction, and synthesis steps, and (3) the script that is used to plot the data.

5 RESULTS

This section presents the results of the SLR. We start by describing the characteristics of the studies that are rejected (Section 5.1) and selected (Section 5.2) as primary studies. Afterward, we discuss the label distributions of the primary studies (Section 5.3). Then, we present the main software-driven strategies to reduce the energy footprint of DCs and, hence, answer **RQ** (Section 5.4). Moreover, we describe the label distribution for each subset of studies belonging to a certain strategy type (Section 5.5). Last, we compare the label distributions among the strategies types (Section 5.6).

[3]https://jupyter.org
[4]https://www.python.org
[5]https://pandas.pydata.org
[6]https://matplotlib.org
[7]https://seaborn.pydata.org

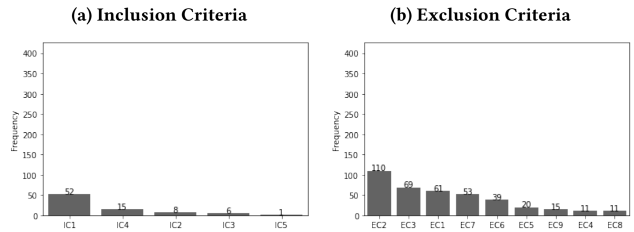

Figure 2: The selection criteria used to reject retrieved studies as primary studies.

5.1 Rejected studies

From the 650 studies that remained after the preprocessing, 224 primary studies are selected. This section describes the characteristics of the 426 studies that are rejected as primary study. Figure 2 presents the selection criteria that are used to reject the studies. We observe that there is not one dominant selection criterion. Note that a study could be rejected based on multiple criteria.

From Figure 2a, we observe that, from the **ICs**, most studies are rejected based on **IC1**. These are studies that did not actually present a strategy to reduce the energy footprint of a DC. Such studies often conduct research around another topic (e.g., security) that involves the term ‘energy’ (e.g., energy-theft) but does not aim to reduce the energy footprint. The other **ICs** are not frequently used to exclude a study.

Moving on to the **ECs**, Figure 2b shows that **EC2** (supporting equipment), **EC2** (hardware), and **EC3** (energy generation, transformation, or supply) are most frequently used to reject studies. These topics are interesting to find strategies to reduce the energy footprint. However, in the current research, they are out of scope. Next, relatively many studies are rejected based on **EC7**. This includes the studies that were not considered due to their form (e.g., book, poster).

5.2 Primary studies

This section describes the characteristics of the 224 primary studies. A full list of the title, authors, publication year, and venue of the primary studies is presented in Appendix C. Figure 3 presents some characteristics of the primary studies.

From Figure 3a, we learn that most studies were Journal (J) articles, 30% of the studies are presented on a Conference (C), and solely 1 study is presented in a Workshop (W).

Next, we observe from Figure 3b that the most frequently used venue to publish articles around the theme energy footprint of DCs is `IEEE Xplore`[8]. Other popular venues are `Springer`[9] and `Elsevier`[10].

Last, Figure 3c shows that most studies were published in the year 2019. Surprisingly, in 2020 the topic became less popular as the number of studies published is almost half compared to 2019. The query was executed in January of 2021 and hence this number is (hopefully) still growing.

[8]https://ieeexplore.ieee.org
[9]https://www.springer.com
[10]https://www.elsevier.com

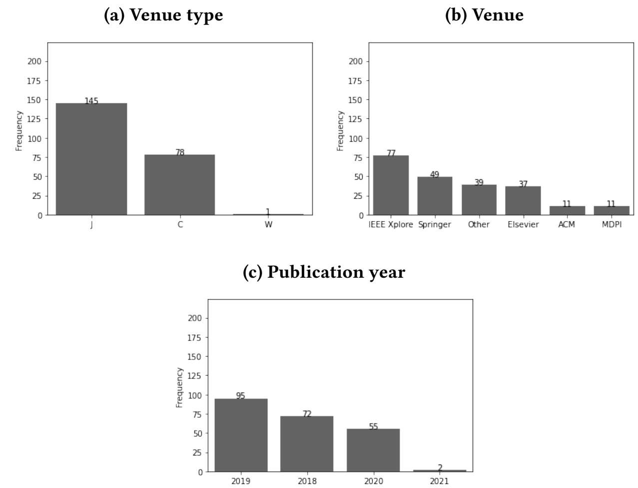

Figure 3: The characteristics of the primary studies.

5.3 Label distribution of the primary studies

In Figure 4 an overview is presented of the label distribution for each category of the primary studies. The plots are scaled according to the number of studies. In Sections 5.3.1 - 5.3.9, we discuss the label distribution per category.

5.3.1 Energy related goal (Figure 4a). From the primary studies, the most frequently mentioned *Energy related goal* is `Reduce energy` which is closely followed by `Increase EE`. During the synthesis, it is often difficult to distinguish these energy related goals as the studies frequently describe their strategy as “Energy-efficient", when in practice the strategy reduces the absolute amount of energy. According to our definition, we do not classify this as energy efficiency. Our strategy is to classify the energy related goal according to our definition rather than the terminology used in the study.

The other energy related goals, namely `Monitor`, `Renewable` and `Reduce costs` were less frequently mentioned. We conjecture that the energy related goal to optimize the renewable energy is more frequently used in strategies that apply to supporting and energy equipment rather than ICT equipment. The renewable energy- and software-driven strategies that we encountered mainly focused on scheduling tasks in geo-distributed DCs depending on the available amount of renewable energy. Last, the strategy Reduce costs was only included in this SLR if the strategy is combined with reducing the energy footprint. Strategies that merely aimed to reduce the costs without reducing the footprint are rejected as primary studies.

5.3.2 Strategy type (Figure 4b). The most frequently discussed *Strategy type* is `VM consolidation`. The main steps of VM consolidation, namely `VM selection`, `VM placement`, and `VM migration` are always used in combination with the label VM consolidation. Hence the total number of VM consolidation strategies is 100 regardless of the frequencies its sub-steps. It is interesting to see that VM placement is most frequently discussed sub-step of Vm consolidation.

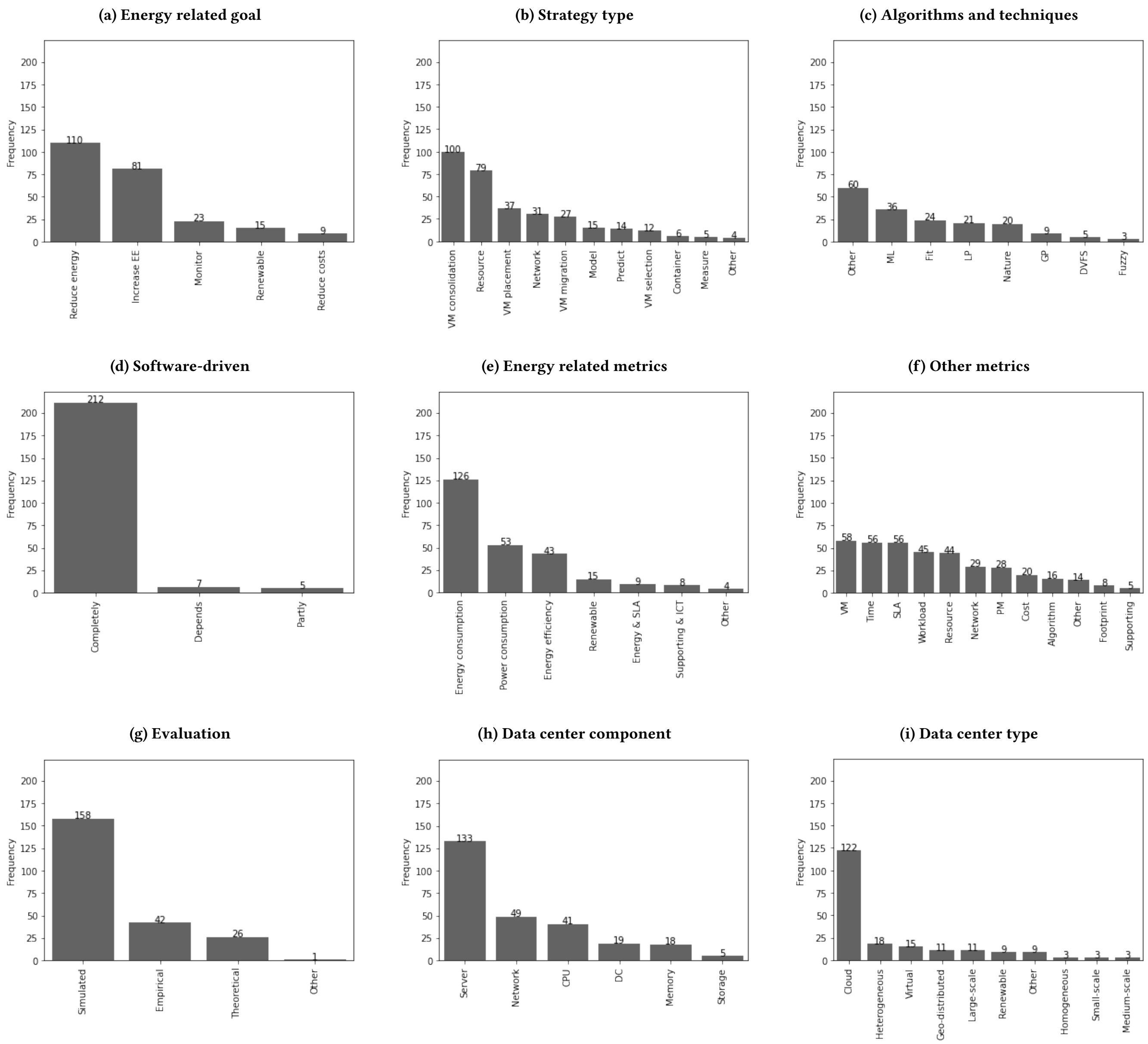

Figure 4: Label distribution of all primary studies.

The strategy *Resource* management is the second largest strategy. We do acknowledge that this strategy is rather broad. This strategy mainly involves task scheduling, workload allocation, and resource optimization strategies. We were unable to find convincing definitions to break down this category. Further research is required to define possible sub-categories. To answer **RQ**, we merged the some strategies and further explain them in Section 5.4.

5.3.3 Algorithms and techniques (Figure 4c). This category was relatively difficult to classify as many custom algorithms were introduced of which we could not find an appropriate classification. Moreover, covered such a broad range of strategies caused the algorithms and techniques to be quite diverse. Further research should be conducted to define relevant algorithms and techniques for a particular strategy. For instance, the work of Dhanoa [7] presents an in-depth study of the algorithms and techniques for the strategies VM VM placement. Therefore, the classification shows a relatively high ratio of `Other` algorithms and techniques and a low ratio of the remaining algorithms and techniques. `ML` is the most frequently used algorithm or technique, this could be due to the popularity and wide scope of this technique.

5.3.4 Software-driven (Figure 4d). The objective of this category is to define the concept software-driven in the context of energy footprint reduction strategies. Our approach is to capture the relation between the strategy and software. The possible relations that we identified were were: (1) the strategy completely consists of software, (2) the strategy depends on software (e.g., when the strategy requires models or calculations enabled by software), and (3) the strategy partly consists of software (e.g., when the strategy consists of software but requires specific hardware). From the results, we observe that the relationship `Completely consists of` is by far the most frequently adapted relation towards software. Hence, most software-driven strategies completely consist of computer code.

5.3.5 Energy related metrics (Figure 4e). The next category is *Energy related metrics*. The most frequently used metric is `Energy consumption`. The metrics captured by this label are mainly expressed in Joules/KWh and measure the absolute amount of energy. In the studies, this metric is mostly used to compare the energy usage before and after applying the strategy. The other most popular metrics are `Power consumption` and `Energy efficiency`. These are related metrics but with a different emphasis.

We observe that the other, more specific, metrics are less frequently used to assess the performance of the strategies. The `Supporting & ICT` metrics show the relation between the energy used for the supporting equipment and energy used for the ICT equipment. The most adapted example is the PUE. Despite its popularity, it is not frequently used in this dataset. We conjecture that is due to our focus on the ICT equipment rather than the supporting equipment to which these metrics are more relevant.

5.3.6 Other metrics (Figure 4f). For the *Other (not energy-related) metrics*, we classified a diverse range of metrics of which none is dominant. The most frequently mentioned metrics are `VM-related` (e.g., number of migrations), this can be explained by VM consolidation being the most popular strategy. The relatively high number of SLA-related metrics can be explained by the relatively high number of studies considering cloud DCs (see Figure 4i). Surprising is the relatively low number of studies reporting the `Footprint`-related metrics (e.g., carbon emissions). Despite many studies report the intention to reduce energy to lower the environmental impact, not many studies actually calculate the gain in environmental benefit and solely report the reduction in energy or the gain in renewable energy usage. The relatively low frequencies for cost- and supporting equipment-related metrics can be explained by our research scope.

5.3.7 Evaluation (Figure 4g). Next, we recorded the *Evaluation* technique that the studies used to evaluate the strategy. Most studies used `CloudSim`[11] to simulate the DC and assess the performance of the strategy. Approximately a quarter of the studies evaluated the strategy in an actual DC. Last, a relatively small proportion of the studies provided a theoretical evaluation. An example of such an evaluation is mathematical proof to show the optimal distribution of tasks among resources. We encountered one `Other` evaluation method, namely, in article [10] where the authors qualitatively assessed the strategy using interviews.

[11]https://github.com/Cloudslab/cloudsim

5.3.8 Data center component (Figure 4h). Next, we recorded of which hardware component the energy is considered. Most strategies consider the server and often measure the energy usage of the CPU and memory to represent the energy usage of the server. Approximately a quarter of the studies considers the network. This proportion corresponds to the proportion of network-related strategy types and network-related metrics. The energy usage of the storage is not often considered. A small proportion of the studies considers the energy usage of the overall DC. These were mainly the studies that introduced strategies aimed at optimizing the use of renewable energy. We conjecture that this small proportion is due to our focus on ICT equipment rather than the supporting/energy equipment.

5.3.9 Data center type (Figure 4i). The only *Data center type* that is relatively frequently discussed is `Cloud`. Cloud DCs are often large DCs and, thus, use relatively much energy. Hence, this explains the motive of reducing the energy footprint (and costs) in cloud DCs. The other labels are all relatively few times encountered. Regarding the labels `Large`-, `Medium`-, and `Small`-scale, we adhered to the terms described in the study and did not define this classification ourselves. Hence, these labels are rather subjective as one study describing the DC as Large could be different from the terminology of another study. Further research is required to define these terms (e.g., in terms of number of servers) and classify the studies accordingly. The `Other` labels mainly captured DCs with specific network topologies or requirements. `Geo-distributed` DCs were often described in the context of tasks scheduling strategies based on the available renewable energy in the different location.

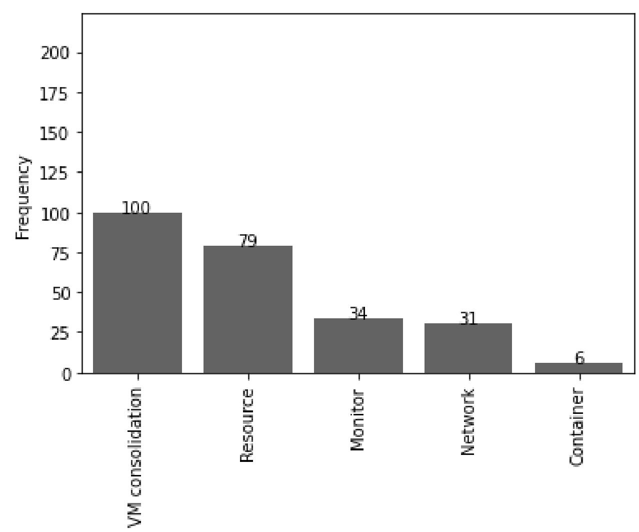

Figure 5: Software-driven strategies to reduce the energy footprint of data centers.

5.4 Software-driven strategies to reduce the energy footprint

We decided to merge some strategies together to get a concise overview of the software-driven strategies to reduce the energy footprint of DCs and, hence, answering **RQ**. Figure 5 shows the distribution of the merged strategies. Note some studies describe multiple strategies and as we kept track of the number of labels rather than the number of studies, the total number of labels exceeds the total number of primary studies.

We observe that *VM consolidation* is the most frequently discussed strategy and is is described in approximately half of the primary studies. We merged the strategies *VM selection*, *VM migration*, and *VM placement* into this category as the latter are sub-steps of VM consolidation. To prevent biased result we counted a study labeled as 'VM consolidation, VM placement' once within the super class VM consolidation.

The next strategy is *Resource management*, this strategy is mentioned in 79 studies. As previously mentioned, this category could be redefined into multiple sub-categories such as task scheduling and workload allocation. Further research is required to define criteria that distinguish these related concepts.

The strategy *Monitor* combines all the strategies *Predict*, *Model*, and *Measure*. This is a relatively small proportion of strategies comparable to the share of *Network optimization* strategies.

The strategy that is least frequently discussed is *Container consolidation*. This can be explained by the fact that it is a relatively new technique. It is a promising strategy as it reduces the overhead of separate operating systems for each VM in the strategy VM consolidation.

5.5 Label distribution per strategy type

After defining the main strategy types, we plotted the label distribution per strategy type to understand which concepts are related to certain strategy types. These plots are shown in Appendix B, Figures 6 - 10. Due to the large number of plots, we focus on describing the remarkable findings. In Sections 5.5.1 - 5.5.5, we discuss the label distributions of the primary studies grouped per strategy.

5.5.1 VM consolidation (Figure 6). There are 100 studies that introduce a strategy that is classified as VM consolidation. Hence, the plots are scaled on the range 0 - 100. For the strategy VM consolidation, most *Energy related goals* are to `Reduce the energy` or `Increase the EE`. Only a minor share of the studies focuses on the remaining energy related goals. Regarding the category *Software-driven*, almost all studies (except one) consist completely of software. The used *Energy related metrics* are mainly labeled as `Energy consumption`. `Renewable energy` related metrics are relatively rare in contrast to VM- and SLA-related metrics. This can be explained by the high number of cloud DCs that are the focus point for VM consolidation strategies. The studies mainly focus on the server. Last, the vast majority (approximately 70%) of the considered DCs are cloud DCs.

5.5.2 Resource management (Figure 7). Interestingly, the most frequently *Energy related goal* is to `Increase the EE`. Furthermore, `ML` are relatively popular as they occur more frequently than the `Other` label. Contradicting is that even though the most frequently mentioned Energy related goal is Increase EE, the energy efficiency metrics are less than half of the metrics related to the energy consumption. This emphasizes our previously mentioned discussion that energy efficiency is often defined differently. The most frequently used other metrics are workload- and resource-related.

5.5.3 Monitor (Figure 8). As expected, the vast majority of the studies with the strategy Monitor present the *Energy related goal* monitor. The sub-strategies of the super-strategy Monitor, namely, *Predict*, *Measure*, and *Model* are distributed as follows: most strategies are modeling or predicting the energy usage. The strategy Measure is has a relatively low frequency. There is quite some overlap as these strategies are often used together. For instance, the strategy introduced in the study first describes a method to predict and/or measure the energy consumption and accordingly combines this in a model. This could be due to the measurements relating to sensors are mostly hard-ware oriented. Surprisingly, none of the studies that have the strategy Monitor, focus on the network. We identify this as future research. We observe that a relatively large share of these studies depend on software or partly consists of software. This can be explained by modeling strategies mostly depending on the software to retrieve the data or require specific sensors to measure the energy flows. It is interesting to see that from the *Other metrics*, the most frequently used metric is `Algorithm performance` (e.g., accuracy and RMSE). These are related to prediction algorithms and ML techniques. Last, regarding the *Evaluation*, the label `Simulated` accounts for the largest share although the `Theoretical` closely follows. The studies following this strategy are mostly focused on the complete DC.

5.5.4 Network optimization (Figure 9). The strategy Network optimization only has as *Energy related goals* `Increase EE` and `Reduce energy`. Therefore, *Energy related goals* `Monitor`, `Reduce costs`, and `Renewable` are not found in relation to Network optimization. We observe that the most frequently used *Algorithm/Technique* is `LP`. The *Energy related metrics* only consider the `Energy consumption`, `Energy efficiency`, and `Power consumption`. More specifics metrics such as `Renewable`, `SLA`- or `Supporting`-related metrics are not considered. As expected, the larges share of the *Other metrics* are `Network`-related (e.g., latency, throughput). Furthermore, the largest part of studies is evaluated by means of a simulation. The part of cloud DC is relatively smaller compared to the studies from the other strategies.

5.5.5 Container consolidation (Figure 10). The last strategy is Container consolidation. Only a small part of the studies (namely 6) introduces this strategy. Hence, the results might not be reliable. The labels used as *Energy related goal* are `Reduce energy` and `Increase EE`. All studies consider cloud DCs.

5.6 Comparison of label distributions among strategy types

In the final part of the Results section, we compare the label distributions among the strategies structured per category. This allows us to have a better insight into which labels belong to a certain strategy compared to the other strategies. In this section, we discuss the Figures 11 - 19 from Appendix B. As these are many plots, we stick to describing the highlights. Note that these figures are already presented in the previous section. However, rather than analyzing the results from the perspective of a certain strategy, we now structure the discussion around the categories. Moreover, the reader should be aware that the plots are scaled according to the number of studies within each category (e.g. 225 primary studies, but 100 studies with strategy VM consolidation). Through this design decision, the proportions and distributions can be more accurately compared. However, comparing plots from different scales can create a biased view.

5.6.1 Energy related goal (Figure 11). In this plot, we compare the label distribution among the various strategies for the category *Energy related goal*. Most strategies have as primary *Energy related goal* `Reduce energy`. However, the strategies *Resource management* and *Network optimization* have as primary Energy related goal `Increase EE`. The Energy related goal `Renewable` is not frequently mentioned except for the strategy Resource management which has a relatively large proportion compared to the distribution of the other strategies.

5.6.2 Strategy type (Figure 12). This figure shows the strategy types categorized per strategy type. This is possible as each study can introduce multiple strategies. Of course, each strategy consists mostly of its own strategy. However, as some studies discuss multiple strategies it is interesting to observe which strategies are most frequently combined. The most interesting observation is that relatively many studies having the strategy Monitor are related to the strategy Resource management as well.

5.6.3 Techniques/Algorithms (Figure 13). The frequencies of each algorithm and techniques are often relatively low. `LP` is the most popular label for the strategy Network optimization. The labels and `Nature` and `Fit` are mostly part of studies introducing VM and Container consolidation strategies. Last, `ML` classified techniques and algorithms are a relatively large part of each strategy.

5.6.4 Software-driven (Figure 14). All strategies have as largest share `Completely` consists of software. The strategy Monitor has as only strategy a relatively large part of the `Depends` and `Partly` relations.

5.6.5 Energy related metrics (Figure 15). `Energy consumption` is the most frequently used energy-related metric, and `Energy efficiency` and `Power consumption` are either on the second or third place for all strategies. This can be explained by these metrics capturing the actual energy used. The other Energy related metrics are a combined, applied, or extended version of these metrics. The strategy monitor has relatively large share of `Supporting & ICT`-related metrics. The strategies VM and Container consolidation have a relatively large share of `Energy & SLA`-related metrics. The label `Renewable` is mostly present for the strategy Resource management.

5.6.6 Other metrics (Figure 16). Neither of the strategies have a large part of the `Footprint` related metrics. Only the strategy Monitor a slightly larger part compared to the other strategies. The strategies VM and Container consolidation have a relatively large share of `VM`- and `SLA`-related metrics. In contrast, the strategy Resource management mainly `Workload` and `Resource`-related metrics. Last, as expected, the strategy Network optimization mainly focuses on `Network`-related metrics.

5.6.7 Evaluation (Figure 17). All strategies are mostly evaluated by means of `Simulation`. This is a relatively inexpensive and reliable way of evaluating the strategy in a DC. The share of `Empirical evaluation` is relatively similar for each strategy. Most notable is the relatively high share of `Theoretical` evaluation for the strategy Monitor. Also, the one `Other` evaluation is part of the strategy Monitor as the authors conducted qualitative research on the usability of an energy dashboard [10].

5.6.8 Data center component (Figure 18). The strategies VM consolidation, Resource management and Container consolidation mostly focus on the `Server`. The strategies Network optimization and Monitor mainly on the overall DC.

5.6.9 Data center type (Figure 19). Cloud is a large percentage of the VM and container consolidation strategies. And a relatively small part of the network optimization. The other labels are only small percentages of the overall studies and hence no striking findings here.

6 DISCUSSION

In the research we investigated the **RQ**: *What are the state-of-the-art software-driven strategies aimed at reducing the energy footprint of DCs?* We identified the strategies: *VM consolidation*, *Resource management*, *Monitor*, *Network optimization*, and *Container consolidation*.

From these strategies, *VM consolidation* is the most discussed in the literature. VM consolidation strategies aim to combine multiple VMs onto a single PM. Consequently, less PMs are idle and can thus be turned off to save energy. For the strategy VM consolidation, we found that the most used metrics are VM- and SLA-related. This relates to the finding that most studies consider cloud DCs and consider the energy consumption of the server.

The second most frequently discussed strategy is related to *Resource management*. An example of such a strategy is a task scheduling algorithm. Resource management should be further defined as related concepts, such as resource allocation, task scheduling, and workload management, are overlapping.

The strategies *Monitor* and *Network optimization* were relatively infrequently introduced. The strategy monitor involves studies that aim to capture the energy flow rather than reducing the energy footprint. Monitoring is a prerequisite to reduce the energy footprint. When aiming to monitor the energy footprint, most studies focused on predicting and modeling the energy footprint. The lack of studies aiming to measure the energy footprint can be explained by this strategy being more hardware-oriented. From our analysis, we found that studies that monitor the energy footprint tend not to focus on the network and mainly use ML algorithms.

The strategy *Network optimization* considers all changes to the network to reduce the energy footprint. Examples are switching off parts of the network that are not used and more efficient routing strategies. The primary energy related goal of studies adapting the strategy network optimization is to increase the energy efficiency. Furthermore, network optimization strategies are not associated with optimizing renewable energy.

Last, the strategy *Container consolidation* was only mentioned in 6 articles out of the 224 primary studies. This can be explained by this strategy using a relatively new technique for which the energy footprint is not well-studied. We suggest that more research is required to understand the relation between the energy footprint and containerization consolidation techniques.

Besides defining the strategies, we extracted other information from the primary studies such as the DC type and energy related goal. From this analysis, we learned that there is relatively much overlap between the energy related goals *reduce energy* and *increase energy efficiency*. We noticed from the studies that these concepts are often poorly defined and used interchangeably in the literature. In contrast, the energy related goals *monitor* and *optimize renewable energy* were relatively infrequently addressed. We conjecture that optimizing renewable energy is currently more related to strategies that optimize the electrical or supporting equipment. Many authors motivate the introduction of strategies to reduce energy consumption by the need to mitigate the negative effects on the environment. Considering this, it is surprising that solely 4% of the primary studies evaluated their strategy using metrics that capture the environmental footprint (e.g., carbon emissions).

In this study, we focused on software-driven strategies. To understand the meaning of software-driven strategies, we extracted the relation between the introduced strategy and software for each primary study. We observed that most frequently software-driven strategies completely consist of software. Examples of such strategies are workload scheduling or consolidation algorithms. We observed that most studies evaluated their strategy through simulation experiments. Last, we experienced difficulties in classifying the algorithms and techniques due to the strategy types being so diverse. For future work, we recommend defining the algorithms and techniques per strategy type rather than for all strategies together.

7 THREATS TO VALIDITY

This section discuses the potential threats to validity as defined in [35] together with measures to mitigate these threats. The threats to validity are structured according to the external validity (Section 7.1), internal validity (Section 7.2), construct validity (Section 7.3), and conclusion validity (Section 7.4).

7.1 External Validity

External validity concerns the generalizability of the study [35]. A potential threat to the external validity is the use of one search engine (Google Scholar) to obtain the initial studies. The threat is mitigated by the choice of search engine. Namely, Google Scholar contains articles published in various venues. Another threat to the construct validity is the rejection of studies that are unavailable to the authors. Fortunately, this is a small part of the overall studies (11 out of 750).

7.2 Internal Validity

Internal validity considers the causality between the review process and outcome [35]. To mitigate this threat, we merely considered peer-reviewed studies which is a well-accepted quality standard for scientific literature. Moreover, we defined our research protocol, which includes the automatic search and selection criteria, in advance to reduce the author's bias. Yet, extracting and labeling data from the selected studies is a subjective process. Moreover, labels can overlap (e.g., increase energy efficiency and reduce energy consumption) and some labels have no universal definition (e.g., large-scale DC). We did not define the labels prior as we aimed to derive the labels from the literature. The advantage of this approach is the studies being leading in obtaining the information. The disadvantage is a more subjective extraction and synthesis process. Having multiple researchers select, extract, and synthesize the data is beneficial as the data and definitions can be verified and discussed. It does, however, risk the internal validity as the researchers might interpret the selection criteria and labels differently. We mitigated this threat by verifying the work of other researchers and frequently discuss findings and ambiguities.

7.3 Construct Validity

Construct validity concerns the generalization of the experiment result to the theory [35]. We mitigated the construct validity by performing an automatic search and by formulating a general search query. The initial studies were manually selected to ensure that all relevant articles are included.

7.4 Conclusion Validity

Conclusion validity concerns the analysis of the results [35]. We reviewed a relatively large number of primary studies. This increases the chance of discovering patterns from the population and thereby reducing the conclusion validity. Moreover, we used a well-adapted method to conduct the SLR as defined in [9].

8 CONCLUSION

The energy footprint of DCs continues to increase over time and emits a significant part of the global GHGEs. Hence, the energy footprint of DCs should be reduced. The objective of this study is to provide an overview of the state-of-the-art software-driven strategies aimed at reducing the energy footprint of the ICT-equipment in DCs. To this end, we performed a SLR. We queried Google Scholar to retrieve related studies published from 2018-2021. Afterward, we selected 224 primary studies based on predefined selection criteria. From these studies, we extracted, synthesized, and visualized the relevant data. We identified five main strategies to reduce the energy footprint, namely: VM consolidation, Resource management, Monitor, Network optimization, and Container consolidation. VM consolidation is the most frequently introduced strategy and Container consolidation the least frequently discussed. We suggest that more research is required to understand the relation between the energy footprint and containerization consolidation techniques. Especially considering the effectiveness of VM consolidation strategies in reducing the energy footprint of DCs. We advise DC owners to focus on VM consolidation techniques as these are well-studied. The main limitation of our study is the lack of comparison among the strategies in terms of effectiveness in reducing the energy footprint. Future research is required to identify benchmarks used to evaluate the effectiveness of the strategies. This is the first step in comparing the energy footprint reduction among the various strategies. Being able to rank the strategies according to their effectiveness can aid DC owners in deciding which strategy to apply.

REFERENCES

[1] Amany Abdelsamea, Elsayed E Hemayed, Hesham Eldeeb, and Hanan Elazhary. 2014. Virtual machine consolidation challenges: A review. *International Journal of Innovation and Applied Studies* 8, 4 (2014), 1504.

[2] Luiz André Barroso and Urs Hölzle. 2009. The datacenter as a computer: An introduction to the design of warehouse-scale machines. *Synthesis lectures on computer architecture* 4, 1 (2009), 1–108.

[3] Lotfi Belkhir and Ahmed Elmeligi. 2018. Assessing ICT global emissions footprint: Trends to 2040 & recommendations. *Journal of Cleaner Production* 177 (2018), 448 – 463. https://doi.org/10.1016/j.jclepro.2017.12.239

[4] X. Chang, S. Yang, Y. Jiang, X. Xie, and X. Tang. 2020. Research on Key Energy-Saving Technologies in Green Data Centers. In *2020 IEEE International Conference on Smart Cloud (SmartCloud)*. 111–115. https://doi.org/10.1109/SmartCloud49737.2020.00029

[5] CISCO. [n.d.]. What Is a Data Center. https://www.cisco.com/c/en/us/solutions/data-center-virtualization/what-is-a-data-center.html. Accessed: 2021-03-09.

[6] M. Dayarathna, Y. Wen, and R. Fan. 2016. Data Center Energy Consumption Modeling: A Survey. *IEEE Communications Surveys Tutorials* 18, 1 (2016), 732–794. https://doi.org/10.1109/COMST.2015.2481183

[7] I. S. Dhanoa. 2019. A Review of Energy Efficient Optimization Techniques for VM Placement in Cloud Data Centers. In *2019 6th International Conference on Computing for Sustainable Global Development (INDIACom)*. 205–209.

[8] S. DIOUANI and H. MEDROMI. 2019. How energy consumption in the cloud data center is calculated. In *2019 International Conference of Computer Science and Renewable Energies (ICCSRE)*. 1–10. https://doi.org/10.1109/ICCSRE.2019.8807458

[9] T. Dyba, T. Dingsoyr, and G. K. Hanssen. 2007. Applying Systematic Reviews to Diverse Study Types: An Experience Report. In *First International Symposium on Empirical Software Engineering and Measurement (ESEM 2007)*. IEEE, 225–234. https://doi.org/10.1109/ESEM.2007.59

[10] Volkan Gizli and Jorge Marx Gómez. 2018. A Framework to Optimize Energy Efficiency in Data Centers Based on Certified KPIs. *Technologies* 6, 3 (2018). https://doi.org/10.3390/technologies6030087

[11] Hang Yuan, C. . J. Kuo, and I. Ahmad. 2010. Energy efficiency in data centers and cloud-based multimedia services: An overview and future directions. In *International Conference on Green Computing*. 375–382. https://doi.org/10.1109/GREENCOMP.2010.5598292

[12] John L Hennessy and David A Patterson. 2011. *Computer architecture: a quantitative approach*. Elsevier.

[13] Nathaniel Horner and Inês Azevedo. 2016. Power usage effectiveness in data centers: overloaded and underachieving. *The Electricity Journal* 29, 4 (2016), 61–69. https://doi.org/10.1016/j.tej.2016.04.011

[14] Pei Huang, Benedetta Copertaro, Xingxing Zhang, Jingchun Shen, Isabelle Löfgren, Mats Rönnelid, Jan Fahlen, Dan Andersson, and Mikael Svanfeldt. 2020. A review of data centers as prosumers in district energy systems: Renewable energy integration and waste heat reuse for district heating. *Applied Energy* 258 (2020), 114109. https://doi.org/10.1016/j.apenergy.2019.114109

[15] International Energy Agency (IEA). 2020. Aviation. https://www.iea.org/reports/aviation. Accessed: 2021-03-26.

[16] Tarandeep Kaur and Inderveer Chana. 2015. Energy Efficiency Techniques in Cloud Computing: A Survey and Taxonomy. *ACM Comput. Surv.* 48, 2, Article 22 (Oct. 2015), 46 pages. https://doi.org/10.1145/2742488

[17] Simon Kemp. 2020. *Digital 2020: Global Digital Overview*. https://datareportal.com/reports/digital-2020-global-digital-overview

[18] F. Khan, H. Anwar, D. Pfahl, and S. Srirama. 2020. Software Techniques for Making Cloud Data Centers Energy-efficient: A Systematic Mapping Study. In *2020 46th Euromicro Conference on Software Engineering and Advanced Applications (SEAA)*. 479–486. https://doi.org/10.1109/SEAA51224.2020.00081

[19] Fanxin Kong and Xue Liu. 2014. A Survey on Green-Energy-Aware Power Management for Datacenters. *ACM Comput. Surv.* 47, 2, Article 30 (Nov. 2014), 38 pages. https://doi.org/10.1145/2642708

[20] Paul M Leonardi. 2020. COVID-19 and the new technologies of organizing: Digital Exhaust, Digital Footprints, and Artificial Intelligence in the Wake of Remote Work. *Journal of Management Studies* (2020). https://doi.org/10.1111/joms.12648

[21] Lijun Liu, Quan Zhang, Zhiqiang (John) Zhai, Chang Yue, and Xiaowei Ma. 2020. State-of-the-art on thermal energy storage technologies in data center. *Energy and Buildings* 226 (2020), 110345. https://doi.org/10.1016/j.enbuild.2020.110345

[22] Georgia Lykou, Despina Mentzelioti, and Dimitris Gritzalis. 2018. A new methodology toward effectively assessing data center sustainability. *Computers & Security* 76 (2018), 327 – 340. https://doi.org/10.1016/j.cose.2017.12.008

[23] Fahimeh Alizadeh Moghaddam, Patricia Lago, and Paola Grosso. 2015. Energy-Efficient Networking Solutions in Cloud-Based Environments: A Systematic Literature Review. *ACM Comput. Surv.* 47, 4, Article 64 (May 2015), 32 pages. https://doi.org/10.1145/2764464

[24] Chayan Nadjahi, Hasna Louahlia, and Stéphane Lemasson. 2018. A review of thermal management and innovative cooling strategies for data center. *Sustainable Computing: Informatics and Systems* 19 (2018), 14 – 28. https://doi.org/10.1016/j.suscom.2018.05.002

[25] Luis Pérez-Lombard, José Ortiz, and David Velázquez. 2013. Revisiting energy efficiency fundamentals. *Energy Efficiency* 6, 2 (2013), 239–254.

[26] B. Prabha, K. Ramesh, and P. N. Renjith. 2021. A Review on Dynamic Virtual Machine Consolidation Approaches for Energy-Efficient Cloud Data Centers. In *Data Intelligence and Cognitive Informatics*, I. Jeena Jacob, Selvanayaki Kolandapalayam Shanmugam, Selwyn Piramuthu, and Przemyslaw Falkowski-Gilski (Eds.). Springer Singapore, Singapore, 761–780.

[27] Giuseppe Procaccianti, Patricia Lago, and Stefano Bevini. 2015. A systematic literature review on energy efficiency in cloud software architectures. *Sustainable Computing: Informatics and Systems* 7 (2015), 2 – 10. https://doi.org/10.1016/j.suscom.2014.11.004

[28] V. D. Reddy, B. Setz, G. S. V. R. K. Rao, G. R. Gangadharan, and M. Aiello. 2017. Metrics for Sustainable Data Centers. *IEEE Transactions on Sustainable Computing* 2, 3 (2017), 290–303. https://doi.org/10.1109/TSUSC.2017.2701883

[29] Andrew s Tanenbaum and David J Wetherall. 2010. Computer Networks. (2010).

[30] K. Shafique, B. A. Khawaja, F. Sabir, S. Qazi, and M. Mustaqim. 2020. Internet of Things (IoT) for Next-Generation Smart Systems: A Review of Current Challenges, Future Trends and Prospects for Emerging 5G-IoT Scenarios. *IEEE Access* 8 (2020), 23022–23040. https://doi.org/10.1109/ACCESS.2020.2970118

[31] Z. Song, X. Zhang, and C. Eriksson. 2015. Data Center Energy and Cost Saving Evaluation. *Energy Procedia* 75 (2015), 1255 – 1260. https://doi.org/10.1016/j.egypro.2015.07.178 Clean, Efficient and Affordable Energy for a Sustainable Future: The 7th International Conference on Applied Energy (ICAE2015).

[32] Mohammed Joda Usman, Abdul Samad Ismail, Gaddafi Abdul-Salaam, Hassan Chizari, Omprakash Kaiwartya, Abdulsalam Yau Gital, Muhammed Abdullahi, Ahmed Aliyu, and Salihu Idi Dishing. 2019. Energy-efficient Nature-Inspired techniques in Cloud computing datacenters. *Telecommunication Systems* 71, 2 (2019), 275–302.

[33] A. Varasteh and M. Goudarzi. 2017. Server Consolidation Techniques in Virtualized Data Centers: A Survey. *IEEE Systems Journal* 11, 2 (2017), 772–783. https://doi.org/10.1109/JSYST.2015.2458273

[34] Thiago Lara Vasques, Pedro Moura, and Aníbal de Almeida. 2019. A review on energy efficiency and demand response with focus on small and medium data centers. *Energy Efficiency* 12, 5 (2019), 1399–1428.

[35] Claes Wohlin, Per Runeson, Martin Höst, Magnus C Ohlsson, Björn Regnell, and Anders Wesslén. 2012. *Experimentation in software engineering*. Springer Science & Business Media.

A DEFINITIONS AND EXAMPLES OF THE LABELS

Category	Label	Definition	Examples of extracted data
Energy related goal	`Reduce energy`	Applying the strategy results in a reduction of the absolute amount of energy.	Reduce energy consumption, reduce power consumption, energy saving.
	`Increase EE`	Increase energy efficiency; applying the strategy results in a more efficient use of the energy (this does not imply an absolute reduction in energy). For instance, more work can be done with the same amount of energy or the energy consumed by core activities is increased relative to the energy consumed by supporting activities. Examples: minimize energy consumption while . . . , trade-off energy and	Trade-off between power consumption and delay performance.
	`Renewable`	Optimize renewable energy; optimize the ratio between green/renewable and brown/exhaustible energy. This includes: minimize brown energy, increase green energy.	Maximize the utilization of renewable energy sources, address the challenges arising from adopting solar powered datacenters.
	`Monitor`	Predict, model, or, measure the energy flows.	Predict energy consumption.
	`Reduce costs`	Reduce energy-related costs. Note that we excluded articles that solely focus on minimizing energy related costs without reducing the energy footprint.	Minimize energy costs.
Strategy type	`Resource`	Resource management; process that deal with the procurement and release of resources. Furthermore, we consider the division and scheduling of tasks and workload among the resources.	Load balancing by improving the process of executing requests.
	`VM consolidation`	Combining multiple VMs into a single PM [1].	Optimization algorithm to assign virtual machines to physical servers.
	`VM selection`	Selecting VMs to migrate from overloaded hosts [1].	VM selection strategy named Minimized Square Root available Resource (MISR).
	`VM migration`	Migrating the VM to the PM with minimal service downtime and resource consumption [1].	Investigate how migration decisions should be made to save energy without any negative impact on the service performance.
	`VM placement`	Placing selected VMs on active or reactivated PMs [1].	Proposing an algorithm for optimal VM placement.
	`Predict`	Predict future energy usage.	Proposing a prediction model for short-term renewable energy production by data centers.
	`Measure`	Measure current energy usage.	Proposing a new measure (EEUI) to assess the degree of energy efficiency of operating servers.
	`Model`	Model current or future energy flows.	Bottom-up approach to quantify past, current, and near future electricity used by worldwide data centers.
	`Network`	Network infrastructure optimization.	Our approach dynamically controls the number of active communication links by turning off and on ports in the network (switches ports and nodes ports).
	`Container`	Container consolidation;	Online solution based on the incremental exploration of the solution space to map containers on the available array of hosts.
Algorithms/ Techniques	`Nature`	Nature-inspired algorithms	Shuffled frog leaping algorithm (SFLA), Migrating Birds Optimization Algorithm (MBOA)
	`ML`	Machine Learning	Markov chain-based prediction approach to identify the over-utilized and under-utilized hosts in the data center.

	`GP`	Genetic Programming	The design of hybrid partheno-genetic algorithm combines the advantages of single parent genetic algorithm and heuristic algorithm, and overcome the disadvantages of traditional genetic algorithm search ability difference, by introducing a single genetic operators and the FFD mutation operator to ensure algorithm in search ability and global convergence of the iterative process.
	`LP`	Linear Programming	The allocation problem is modeled using Integer Linear Programming (ILP) techniques, where models are formulated with the objective of minimizing the total power consumed by the active and idle cores of the servers.
	`DVFS`	Dynamic Voltage and Frequency Scaling	A novel data center workload allocation policy for NTC servers, which also selects the best dynamic voltage and frequency scaling (DVFS) setup.
	`Fuzzy`	Fuzzy logic	The new proactive approach uses multiobjective evolutionary algorithms to learn fuzzy rule-based systems that determine optimal reallocation decisions according to the preferences of the data center operator and a prediction of the load.
	`Fit`	Fit allocation algorithm	Renewable and Total Cost-Aware First-Fit Optimal Frequency VM Placement
Software-driven	`Completely`	The strategy completely consists of software.	VM migration algorithm is realized in software.
	`Partly`	The strategy partly consists of software.	Physical sensors are required for measurement, however, the prediction and analysis are performed by software.
	`Depends`	The strategy depends on software.	Simulation and prediction is enabled by software.
Energy related metrics	`Energy consumption`	Absolute energy consumption (Joules/KWh)	energy consumption (kWh)
	`Power consumption`	Power consumption (Watt)	power consumption (watt)
	`Energy efficiency`	Ratio of energy and workload	energy efficieny (workload/watt)
	`Energy & SLA`	Combined metric between energy and SLA	Energy and SLA Violation (ESV)
	`Renewable`	Metrics related to renewable energy	renewable energy generation (MWh)
	`Supporting & ICT`	Metric that captures the relation between the energy usage of supporting equiPMent and ICT	Power Usage Effectiveness (PUE)
Other metrics	`VM`	VM-related metrics	average number of VM migrations
	`PM`	PM-related metrics	number of active PMs
	`SLA`	Service Level Agreement (SLA)-related metrics	SLATPAH (the percentage of time each active host violated the SLA), SLAPDM (the performance degradation caused by migration), SLAV (SLA violation) = SLAPAH × SLAPDM.
	`Resource`	Resource utilization	CPU utilization (%), Memory utilization (%).
	`Time`	Time-related metrics	Execution time, makespan.
	`Workload`	Workload-related metrics	DC traffic (exabyte/year), Number of tasks
	`Cost`	Cost-related metrics	Energy price ($)
	`Network`	Network-related metrics	Latency, throughput
	`Algorithm`	Algorithm performance-related metrics	Accuracy, Root Mean Square Error (RMSE)
	`Footprint`	Environmental footprint-related metrics	CO2 emissions (tons/year)
	`Supporting`	Metrics related to supporting (non-ICT) equipment	Cooling temperature
Evaluation	`Simulated`	The strategy is evaluated in an simulated environment.	The performance of the proposed method is evaluated using CloudSim simulator.

	`Empirical`	The strategy is evaluated in an actualDC.	The experimental results on real clusters show that EASE can save servers' power consumption [. . .].
	`Theoretical`	The strategy is evaluated using a theoretical theorem or proof.	The model and its usefulness is validated using the generic ILP solver CPLEX.
Data center component	`DC`	The complete DC.	The energy consumption of the whole DC is considered.
	`Server`	A server is a computer designed to process requests and deliver data to another computer over the internet or a local network.	Server
	`CPU`	Central Processing Unit (CPU): The active part of the computer, which contains the datapath and control and which adds numbers, tests numbers, signals I/O devices to activate, and so on [12].	CPU
	`Memory`	The storage area in which programs are kept when they are running and that contains the data needed by the running programs. The memory is built from DRAM chips. DRAM stands for dynamic random access memory [12].	RAM
	`Network`	A collection of computers interconnected by a single technology [29]. Hardware components of a computer network are: cables, routers, hubs, switches, gateways.	Data center networks with K-ary and Fat-Tree multi-rooted topologies.
	`Storage`	Long-term storage.	Disk
Data center type	`Cloud`	Public or enterprise cloud DC.	Multi-tenant public Infrastructure as a Service (IaaS) cloud.
	`Heterogeneous`	The DC contains heterogeneous severs.	Heterogenous data center with high performance (Brawny) servers and low computing capacity but high energy efficient (Whimpy) servers,
	`Homogeneous`	The DC contains homogeneous severs.	Internet Data Center (IDC) with m homogeneous geo-distributed computing nodes.
	`Geo-distributed`	The DC is located in geographically distributed locations.	Two data centers geographically dispersed by 1 km from each other.
	`Renewable`	The DC is (partly) powered by renewable energy.	Datacenter energy needs are satisfied via a hybrid model of renewable and conventional Grid power. Renewable energy is provided via modern photovoltaic (PV) arrays deployed on the rooftop of the datacenter building or in nearby facilities.
	`Virtual`	Virtual data center (vDC)	We design a greedy algorithm for dynamically deployment of vDCs, which converts multi-objective functions into single-objective functions.
	`Large`	Large-scale DC	Large DC with 7600 physical hosts.
	`Medium`	Medium-scale DC	Small- to medium-scale data centers.
	`Small`	Small-scale DC	Small- to medium-scale data centers.

B PLOTS

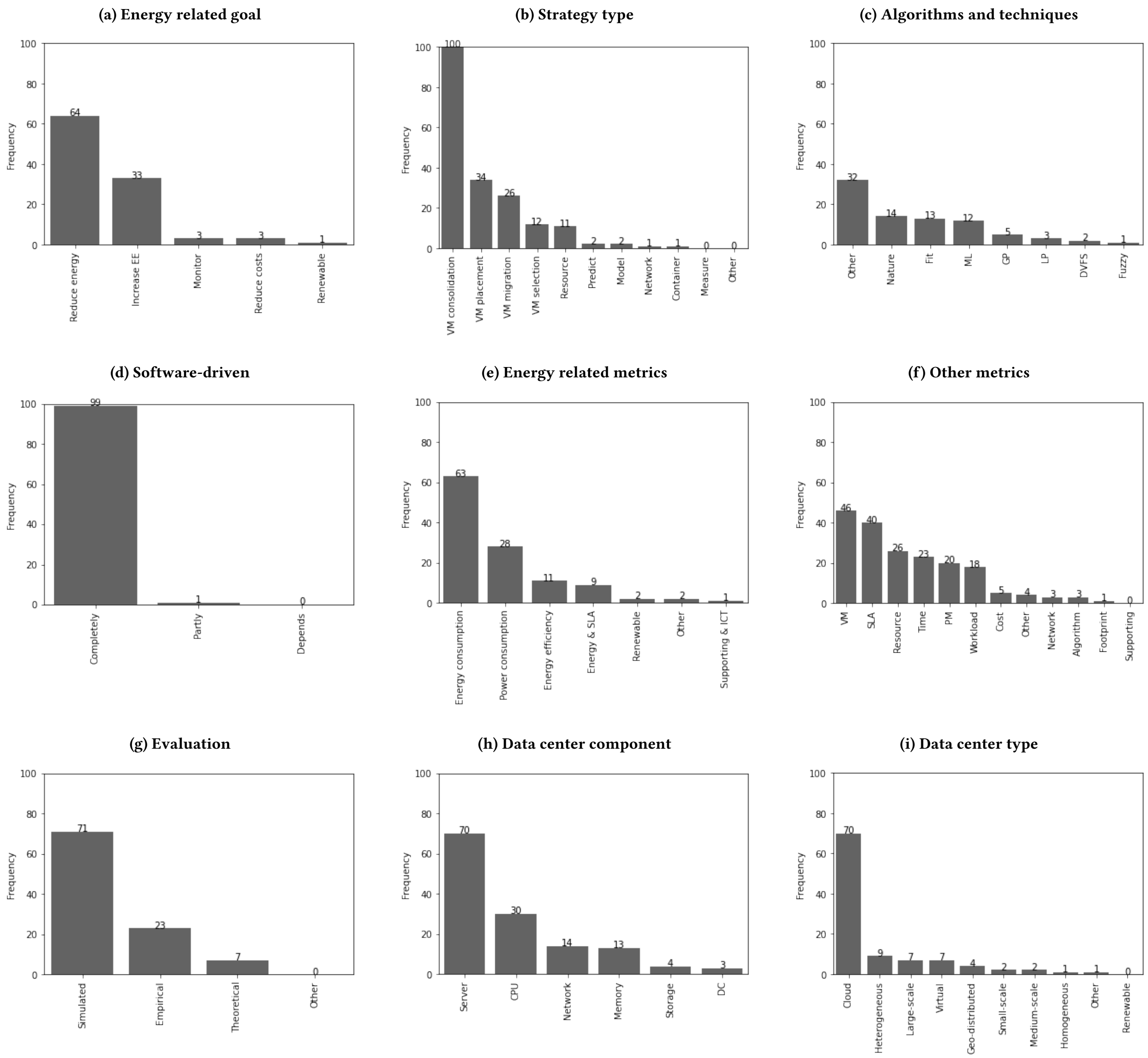

Figure 6: Label distribution of primary studies with strategy: *VM consolidation.*

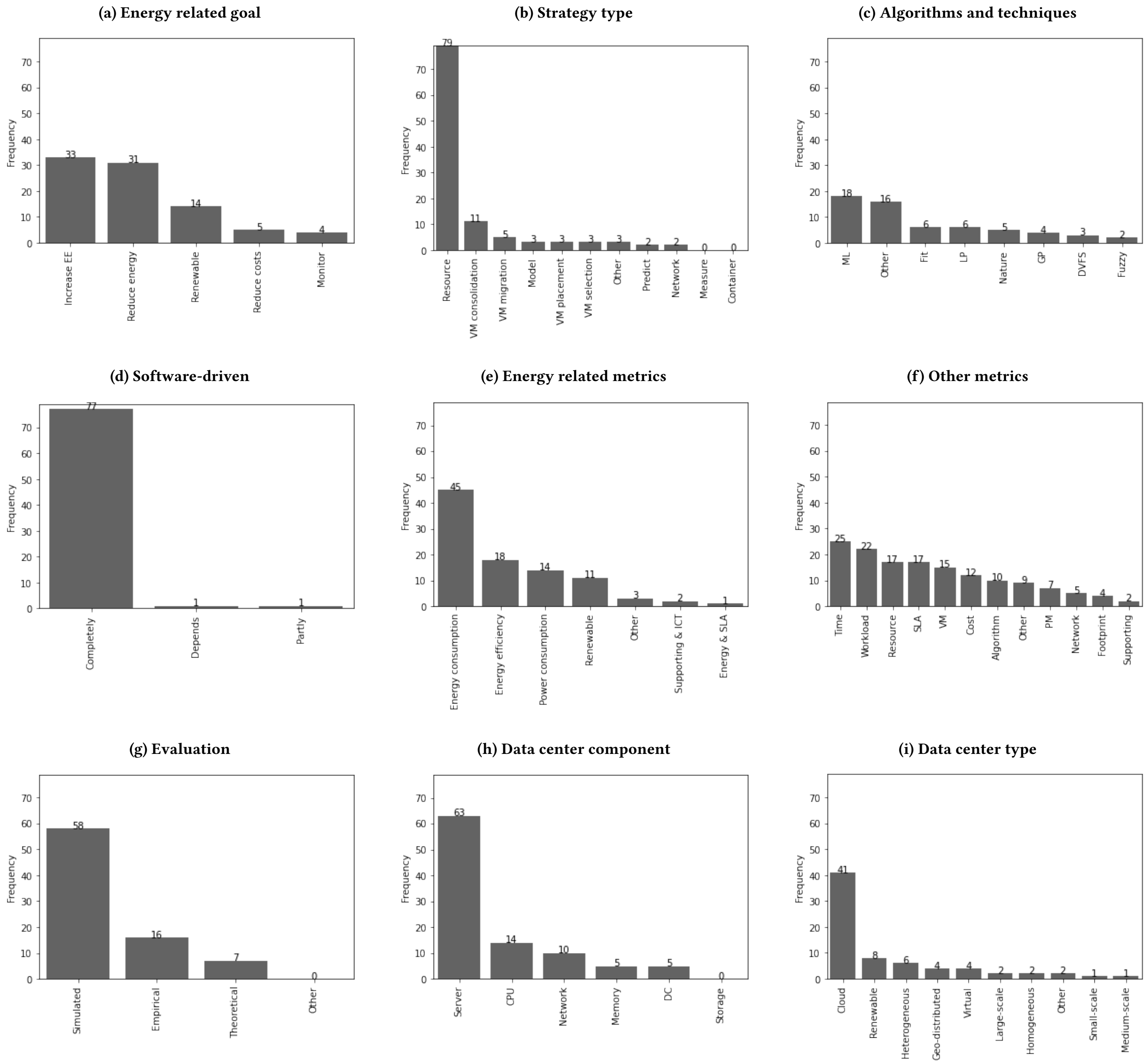

Figure 7: Label distribution of primary studies with strategy: *Resource management*.

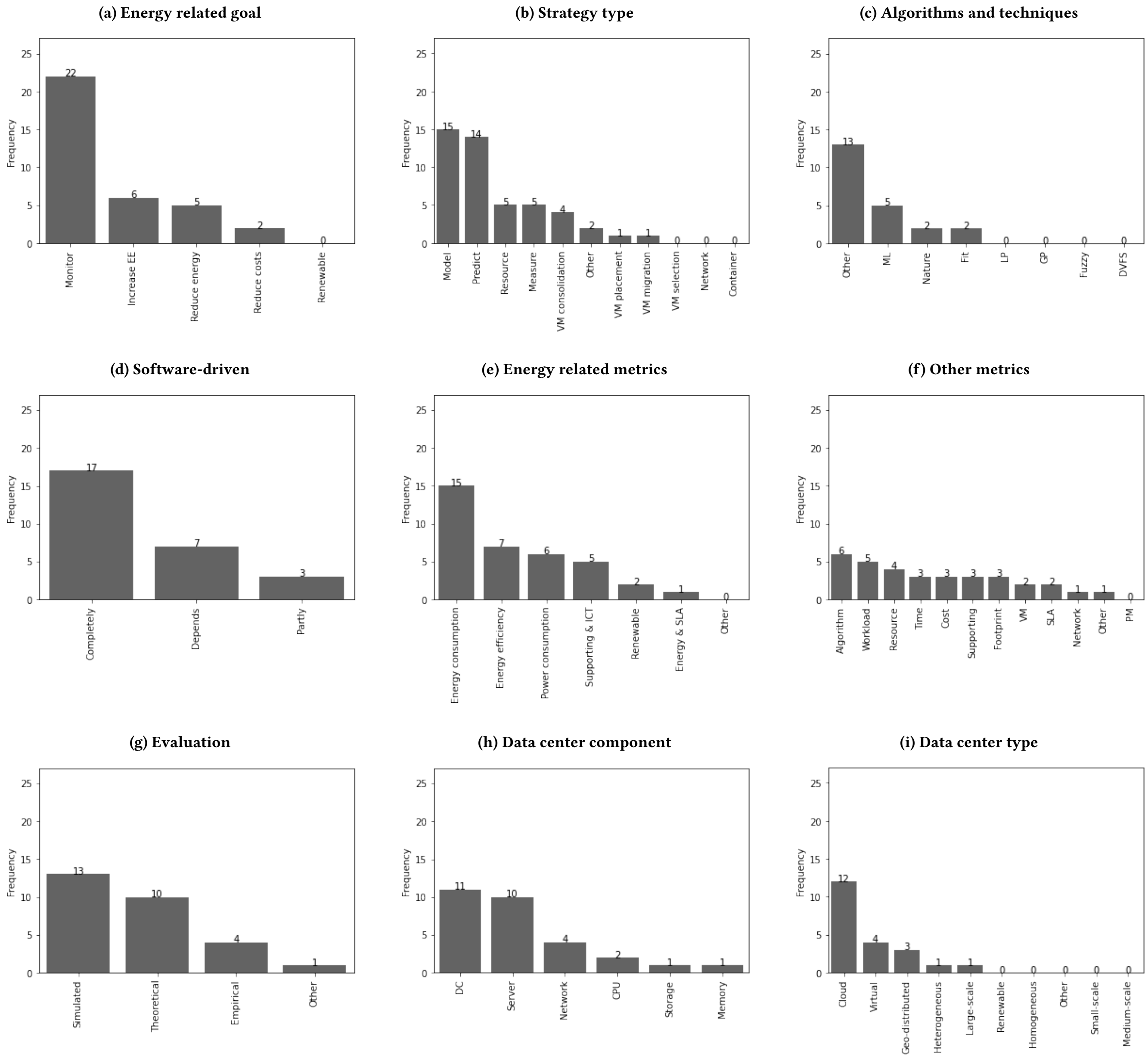

Figure 8: Label distribution of primary studies with strategy: *Monitor*.

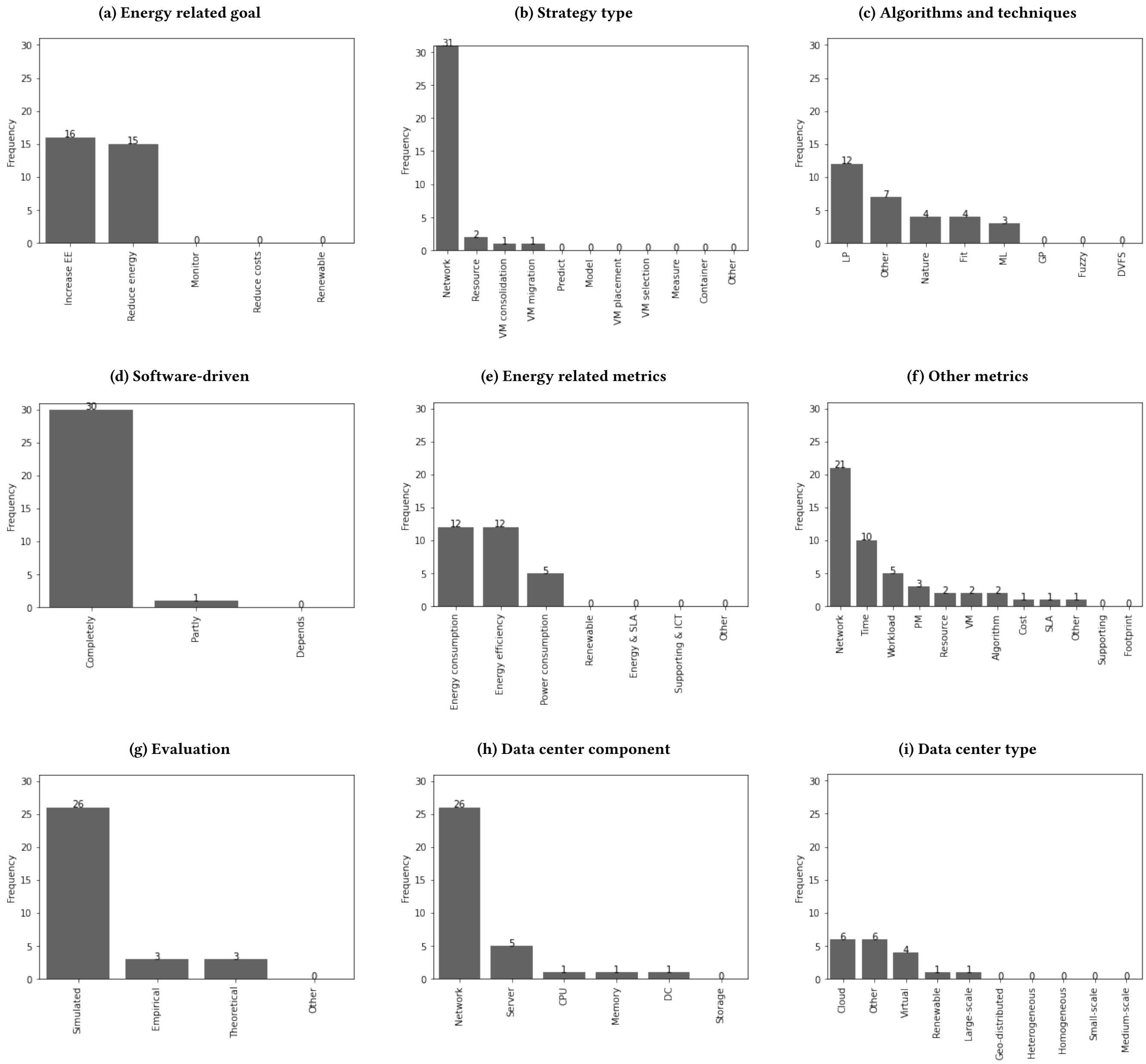

Figure 9: Label distribution of primary studies with strategy: *Network optimization.*

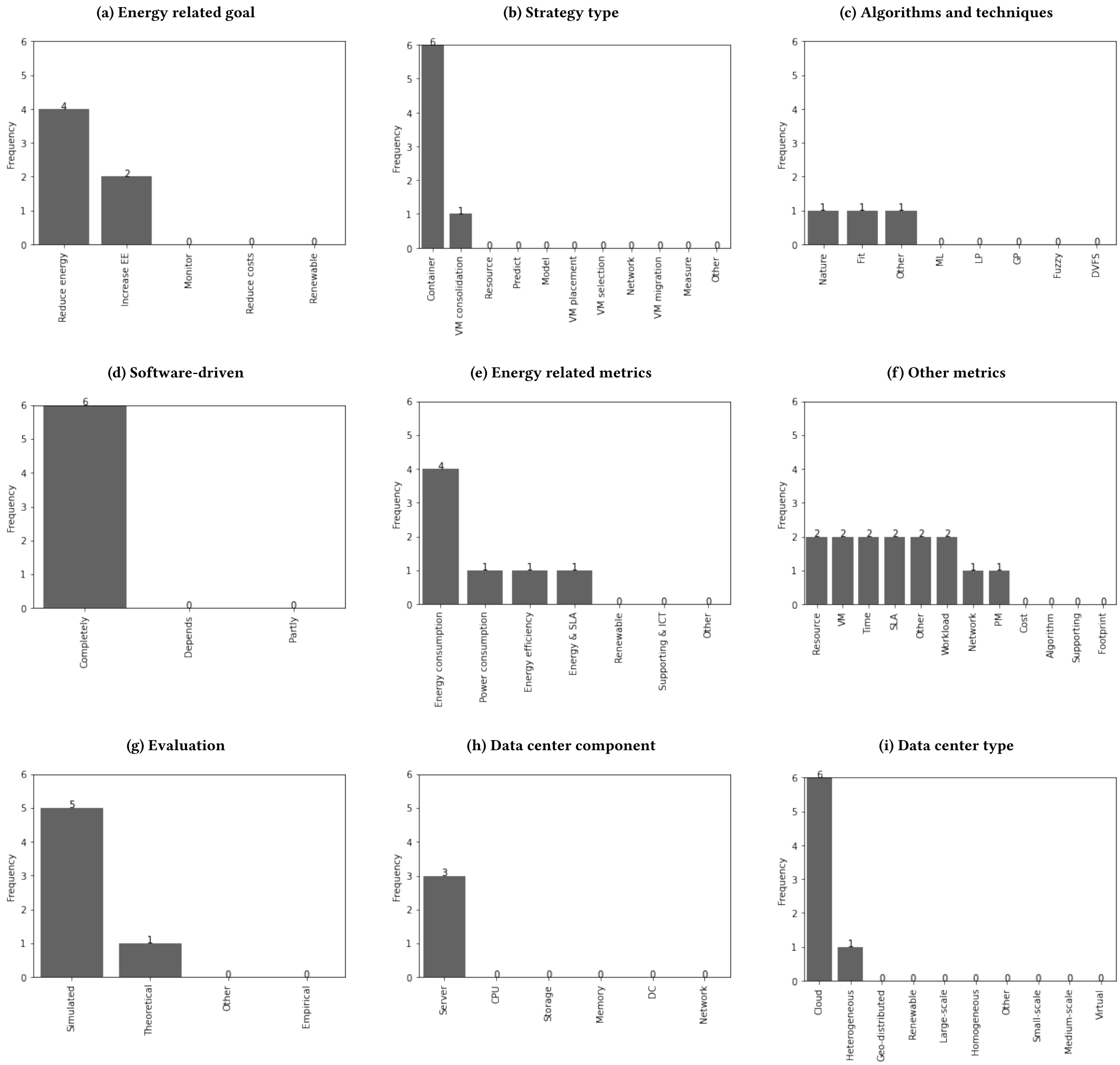

Figure 10: Label distribution of primary studies with strategy: *Container consolidation.*

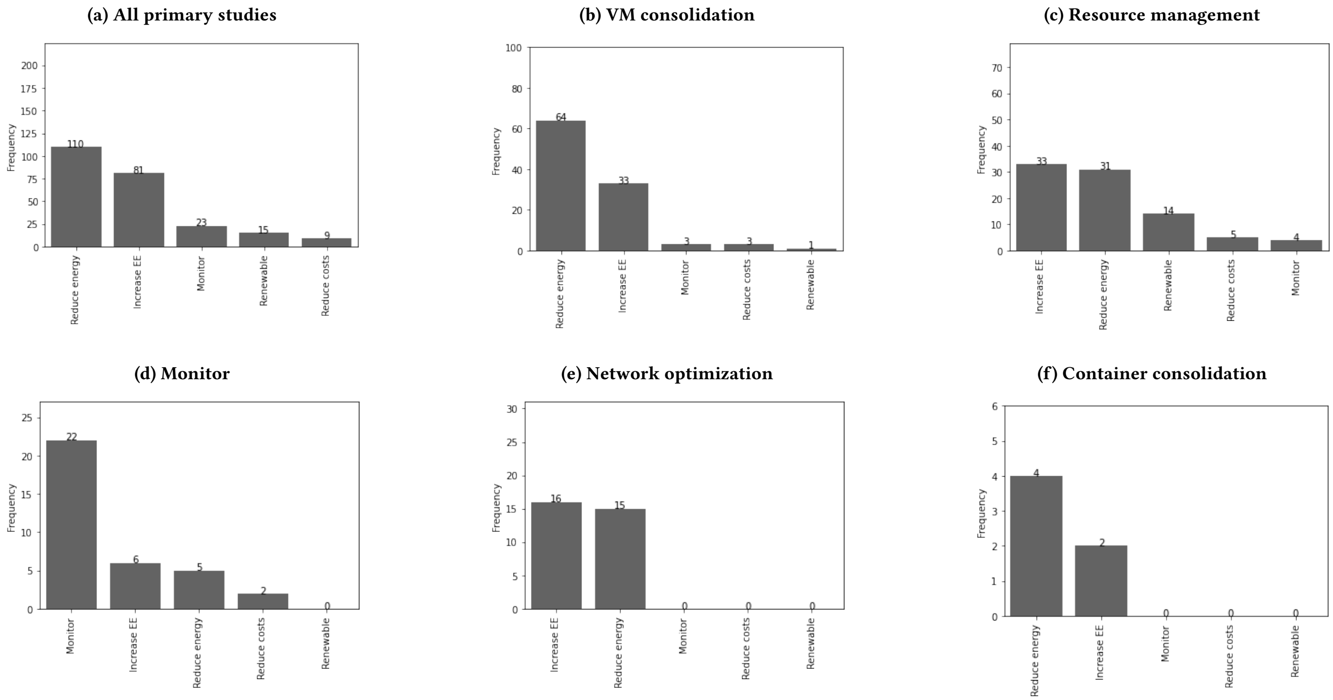

Figure 11: Label distribution for the category *Energy related goal* compared among the strategies.

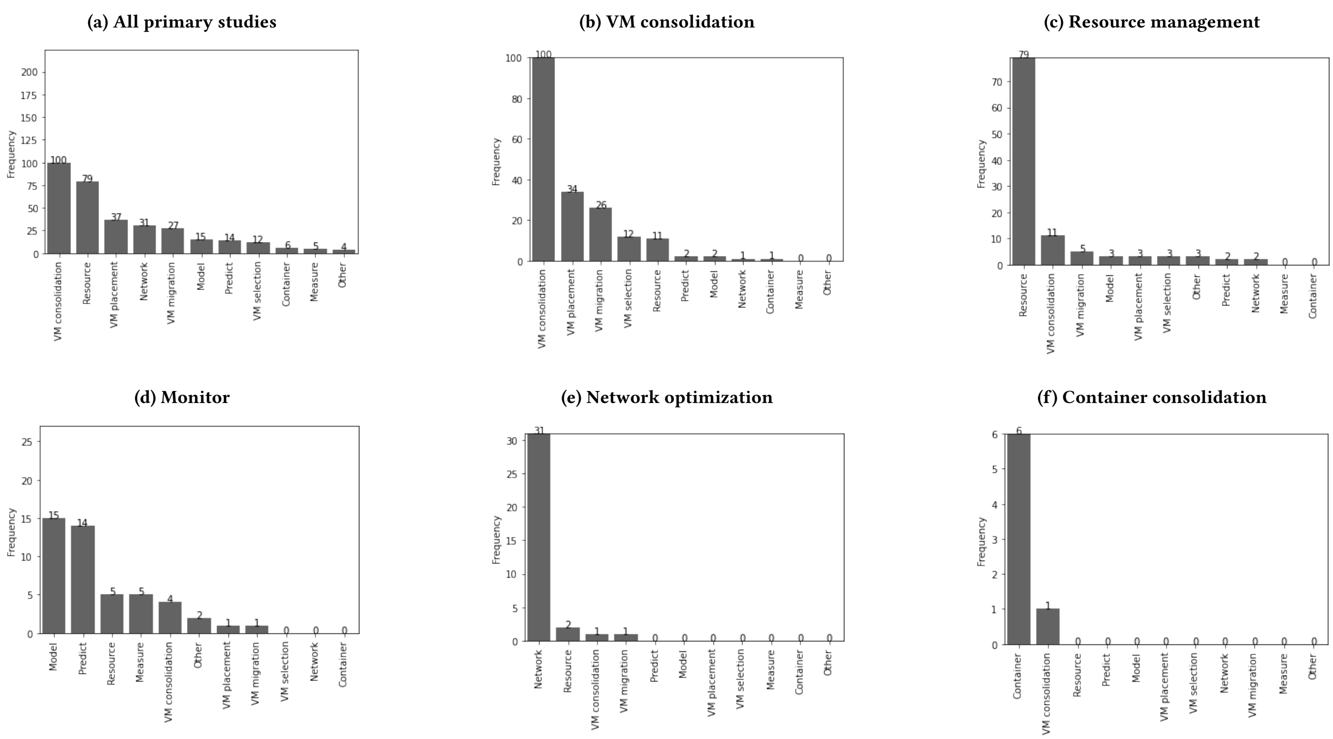

Figure 12: Comparison of the distributions for the category *Strategy type* between the strategies.

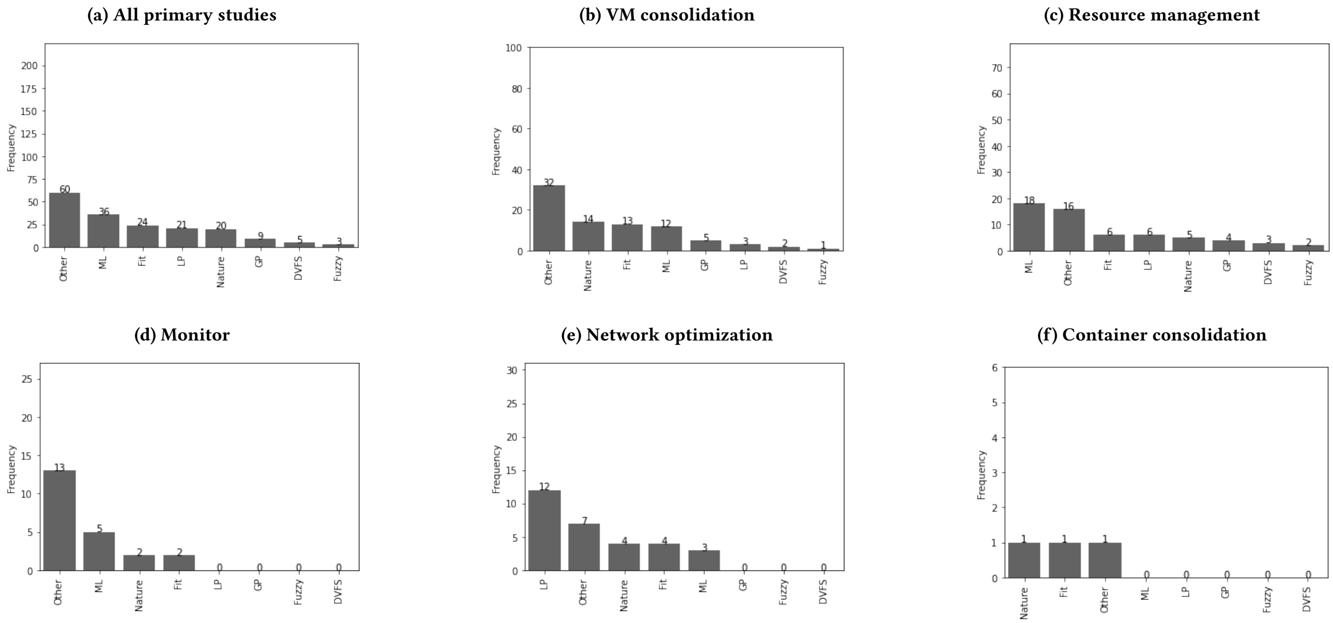

Figure 13: Comparison of the distributions for the category *Algorithms and techniques* between the strategies.

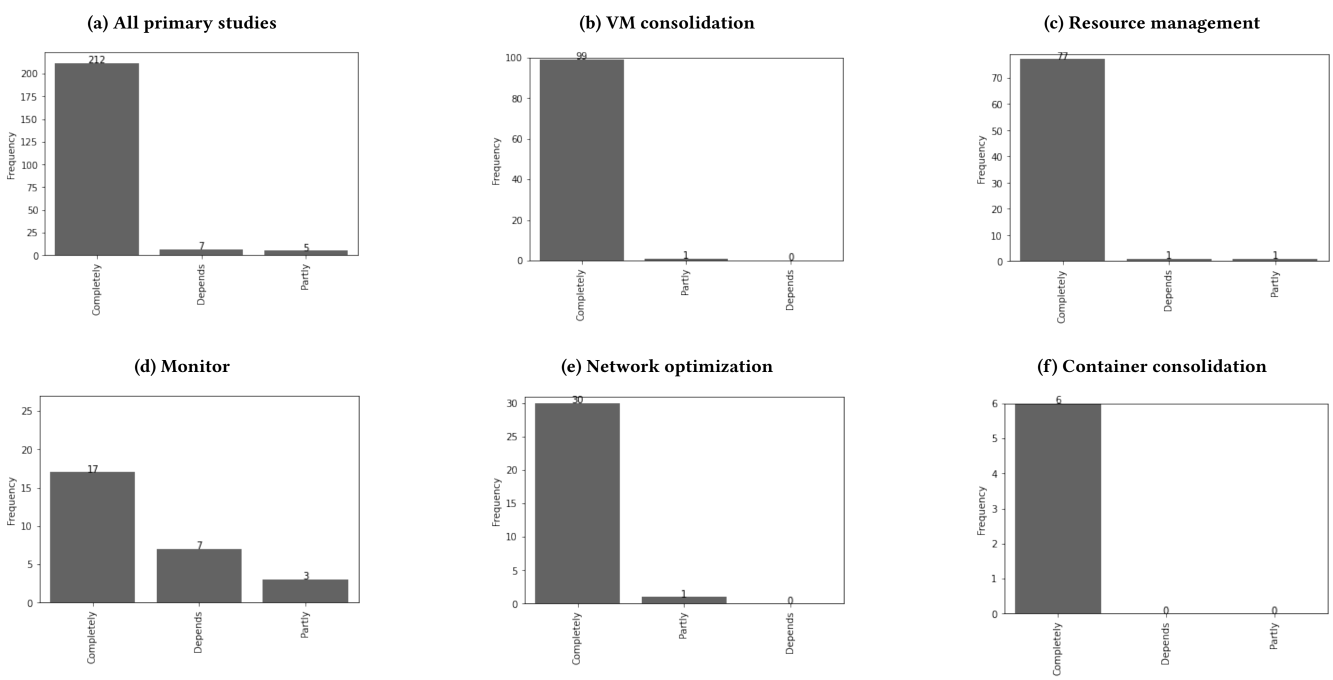

Figure 14: Comparison of the distributions for the category *Software-driven* between the strategies.

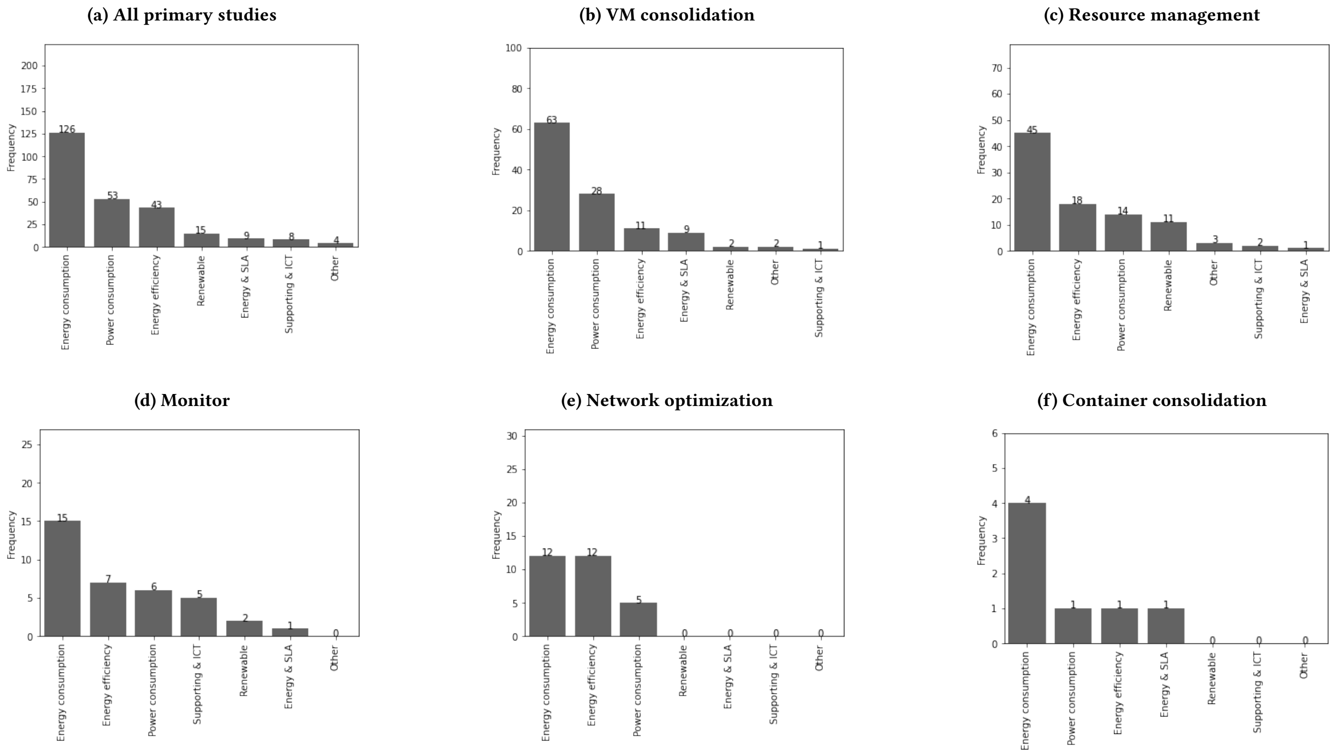

Figure 15: Comparison of the distributions for the category *Energy related metrics* between the strategies.

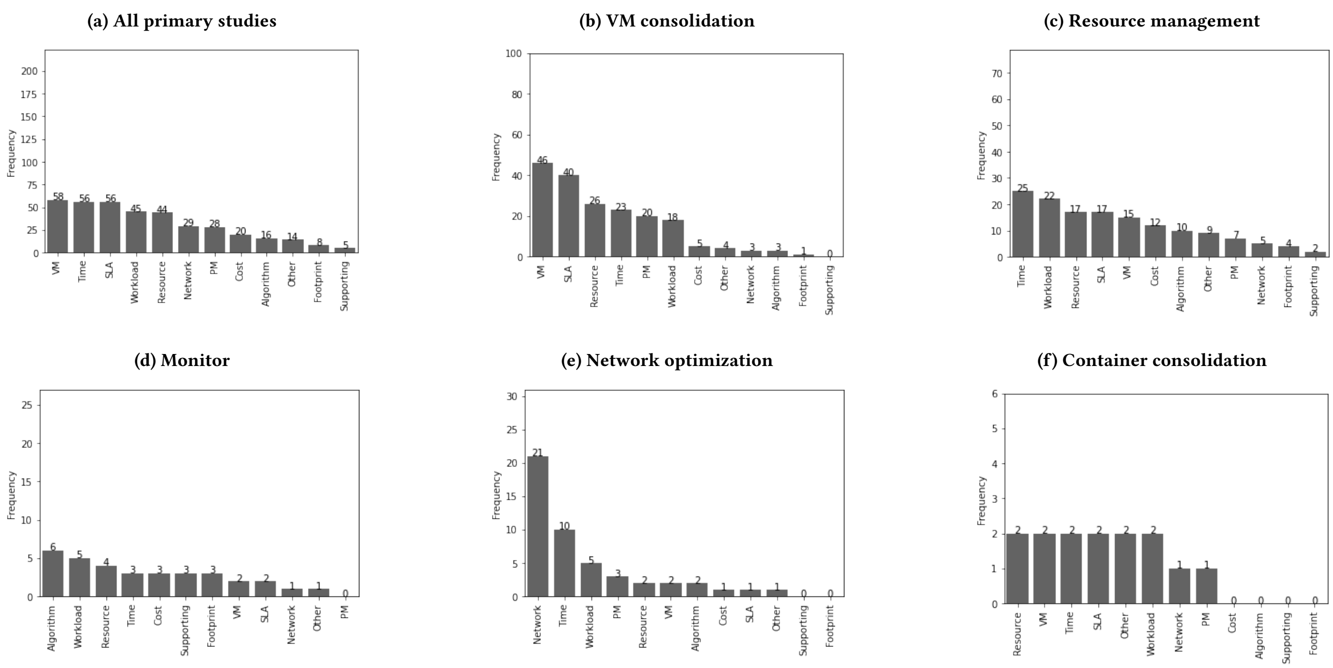

Figure 16: Comparison of the distributions for the category *Other metrics* between the strategies.

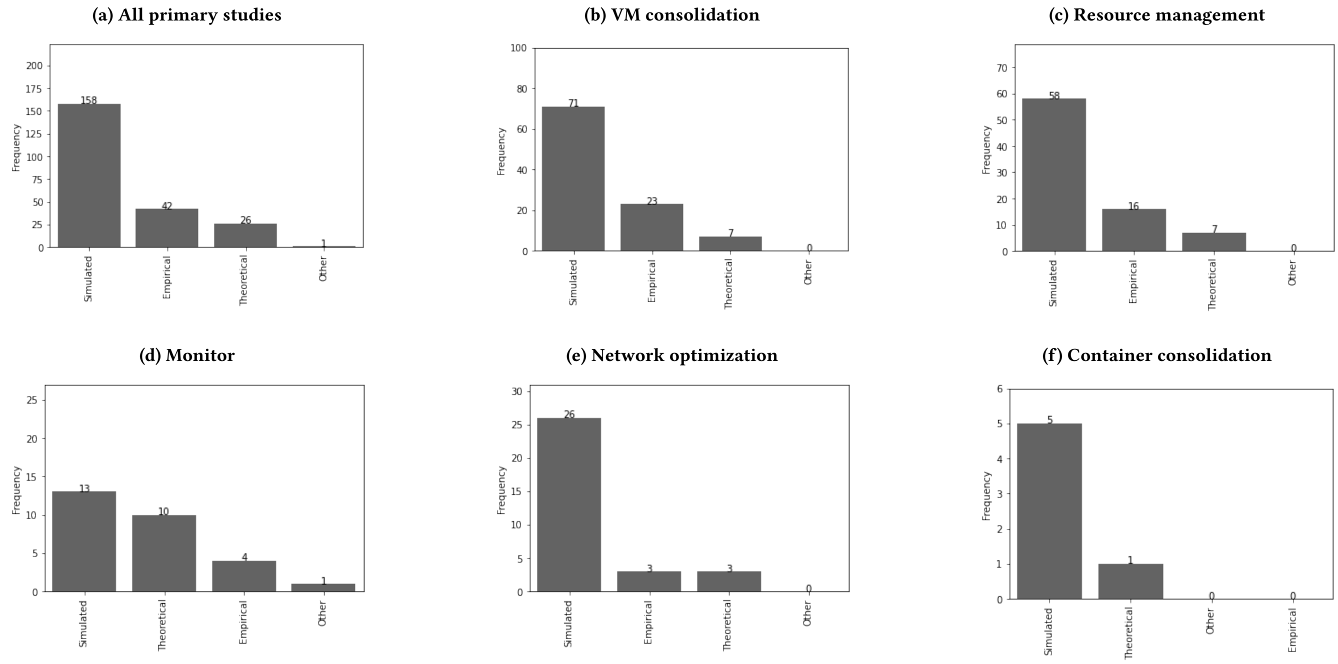

Figure 17: Comparison of the distributions for the category *Evaluation* between the strategies.

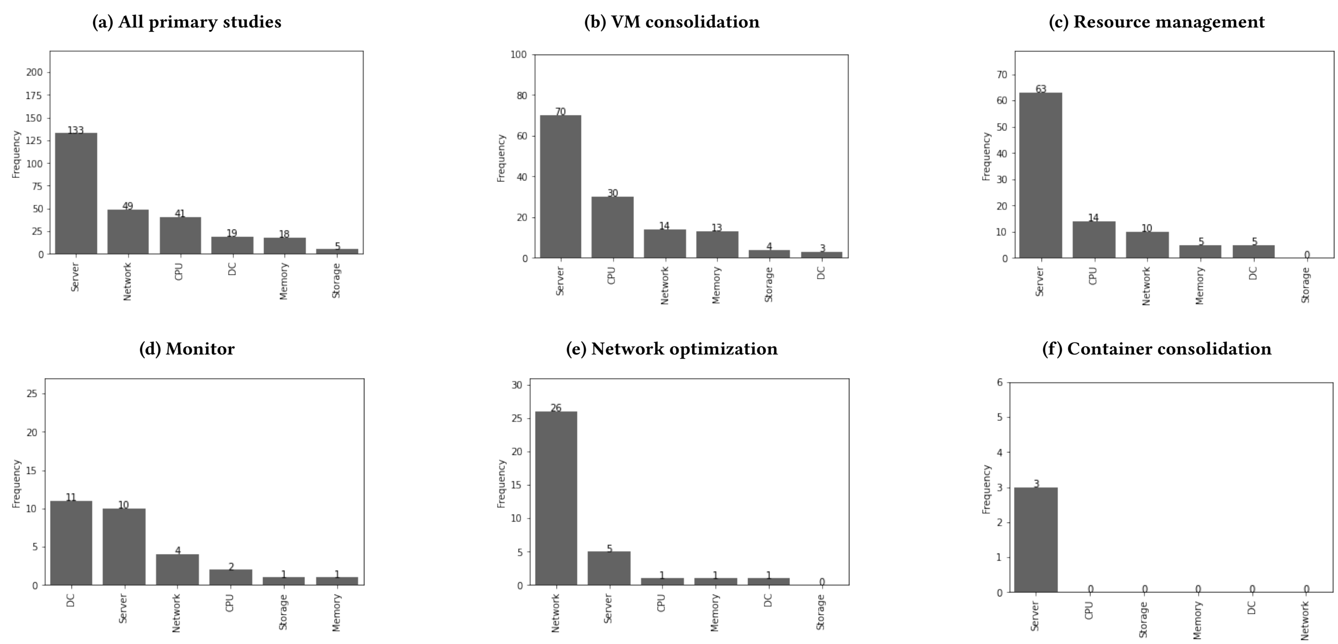

Figure 18: Comparison of the distributions for the category *Data center component* between the strategies.

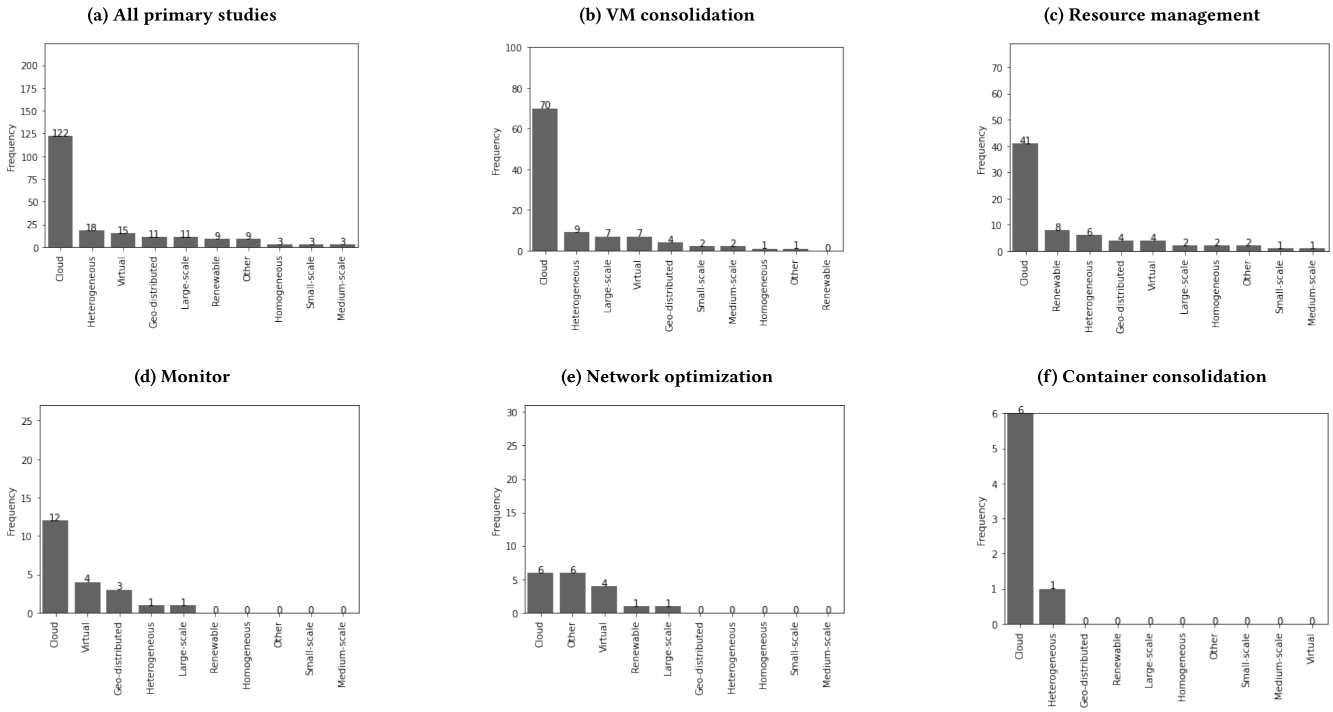

Figure 19: Comparison of the distributions for the category *Data center type* between the strategies.

C PRIMARY STUDIES

Title	Authors	Year	Venue
Green Data Center Analysis and Design for Energy Efficiency Using Clustered and Virtualization Method	JH Moedjahedy, M Taroreh	2019	IEEE
Energy efficient scheduling for cloud data centers using heuristic based migration	GG Kumar, P Vivekanandan	2019	Springer
Load Management with Predictions of Solar Energy Production for Cloud Data Centers	M Floridia, D Laganà, C Mastroianni, M Meo, D Renga	2020	IEEE
Flexibility-Based Energy and Demand Management in Data Centers: A Case Study for Cloud Computing	R Basmadjian	2019	Multidisciplinary Digital Publishing Institute
Predictions and Modeling Energy Consumption for IT Data Center	M Soltane, P Roose, D Makhlouf, K Okba	2018	Springer
An energy-efficient power management for heterogeneous servers in data centers	Q Wang, H Cai, Q Cao, F Wang	2020	Springer
MFF: Performance Interference-Aware VM Placement Algorithm for Reducing Energy Consumption in Data Centers	D Mosoti, VO Omwenga, P Ogao	2020	Open Journal for Information Technology
Network-aware energy saving multi-objective optimization in virtualized data centers	M Al-Tarazi, JM Chang	2019	Springer
Energy efficient resource selection and allocation strategy for virtual machine consolidation in cloud datacenters	Y Chang, C Gu, F Luo, G Fan, W Fu	2018	The Institute of Electronics, Information and Communication Engineers
Energy-efficient task scheduling for data centers with unstable renewable energy: A robust optimization approach	Y Lu, R Wang, P Wang, Y Cao, J Hao, K Zhu	2018	IEEE
Variable neighborhood search-based symbiotic organisms search algorithm for energy-efficient scheduling of virtual machine in cloud data center	M Abdullahi, SI Dishing, MJ Usman	2019	Springer
Optimized Renewable Energy Use in Green Cloud Data Centers	M Xu, AN Toosi, B Bahrani, R Razzaghi, M Singh	2019	Springer
An Energy-aware Routing Mechanism based on MBOA for Data Center Network	Z Jianzhe, S Qingyu, L Guangwei	2019	IEEE
An Energy-Efficient VM migrations optimization in Cloud Data Centers	C Thiam, F Thiam	2019	IEEE
Jointly optimizing the IT and cooling systems for data center energy efficiency based on multi-agent deep reinforcement learning	C Chi, K Ji, A Marahatta, P Song, F Zhang…	2020	ACM
A robust modeling framework for energy analysis of data centers	N Lei	2020	ACM
Exploiting Traffic Correlation Towards Energy Saving in Data Centers	Z Chkirbene, A Gouissem, R Hadjidj, R Hamila, S Foufou	2018	IEEE
Energy and quality of service-aware virtual machine consolidation in a cloud data center	A Tarafdar, M Debnath, S Khatua, RK Das	2020	Springer
A proactive autoscaling and energy-efficient VM allocation framework using online multi-resource neural network for cloud data center	D Saxena, AK Singh	2020	Elsevier
A deep neural network based approach to energy efficiency analysis for cloud data center	HA Ounifi, A Gherbi, N Kara, W Li	2019	IEEE
Availability-Aware Multi-Objective Virtual Cluster Allocation Optimization in Energy-Efficient Datacenters	X Liu, B Cheng, Y Li, J Chen	2019	IEEE
Energy-Efficient Flow Routing and Scheduling in Hybrid Data Center Networks	M Luo, J Li, J Ma, H Li, M Sheng	2019	IEEE
Multi-criteria-Based Energy-Efficient Framework for VM Placement in Cloud Data Centers	N Khattar, J Singh, J Sidhu	2019	Springer
Temperature-aware workload management for sustainable datacenters powered by renewable energy	Y Li, X Wang, P Luo, X Yang	2019	ACM
Real-time energy-conserving VM-provisioning framework for cloud-data centers	S Ismaeel, A Miri	2019	IEEE
Energy consumption optimization scheme of cloud data center based on SDN	Q Liao, Z Wang	2018	Elsevier
Energy-Aware Virtual Data Center Migration	X Ma, Z Zhang, S Su	2019	Journal of Advanced Computational Intelligence and Intelligent Informatics
Profile-guided three-phase virtual resource management for energy efficiency of data centers	Z Ding, YC Tian, M Tang, Y Li, Y Wang, C Zhou	2019	IEEE
Batch Arrival Multiserver Queue with State-Dependent Setup for Energy-Saving Data Center	T Phung-Duc	2020	Springer
Energy efficient virtual machine placement with an improved ant colony optimization over data center networks	W Wei, H Gu, W Lu, T Zhou, X Liu	2019	IEEE
Reducing the operational cost of cloud data centers through renewable energy	D Laganà, C Mastroianni, M Meo, D Renga	2018	Multidisciplinary Digital Publishing Institute
New approach for reducing energy consumption and load balancing in data centers of cloud computing	M Tarahomi, M Izadi	2019	Journal of Intelligent & Fuzzy Systems
Towards Energy Efficient Servers' Utilization in Datacenters	A Osman, A Sagahyroon, R Aburukba, F Aloul	2019	Springer
A Dynamic Energy-saving Deployment Algorithm for Virtual Data Centers	S Han, J Li, Y Ma, Q Dong, D Wu	2019	IEEE
Energy consumption and emission mitigation prediction based on data center traffic and PUE for global data centers	Y Liu, X Wei, J Xiao, Z Liu, Y Xu, Y Tian	2020	Elsevier
Energy efficient VM scheduling and routing in multi-tenant cloud data center	S Ch, T Ramesh	2019	Elsevier
Smartly handling renewable energy instability in supporting a cloud datacenter	J Gao, H Wang, H Shen	2020	IEEE
An experience-based scheme for energy-SLA balance in cloud data centers	X Zhou, K Li, C Liu, K Li	2019	IEEE
Optimizing energy consumption for a performance-aware cloud data center in the public sector	K Chang, S Park, H Kong, W Kim	2018	Elsevier
Integrated network and hosts energy management for cloud data centers	O Al-Jarrah, Z Al-Zoubi, Y Jararweh	2019	Wiley Online Library
EEUI: a new measure to monitor and manage energy efficiency in data centers	F Abaunza, AP Hameri, T Niemi	2018	International Journal of Productivity and Performance Management
CPicker: Leveraging Performance-Equivalent Configurations to Improve Data Center Energy Efficiency	FQ Sun, GH Yan, X He, HW Li, YH Han	2018	Springer
An energy and performance aware consolidation technique for containerized datacenters	AA Khan, M Zakarya, R Buyya, R Khan, M Khan, O Rana	2019	IEEE
Energy-aware coflow and antenna scheduling for hybrid server-centric data center networks	T Li, S Santini	2019	IEEE
A whale optimization system for energy-efficient container placement in data centers	A Al-Moalmi, J Luo, A Salah, K Li, L Yin	2021	Elsevier

Energy-efficient Virtual Machine Allocation Technique Using Flower Pollination Algorithm in Cloud Datacenter: A Panacea to Green Computing	MJ Usman, AS Ismail, H Chizari, G Abdul-Salaam, AM Usman, AY Gital, O Kaiwartya, A Aliyu	2019	Springer
Energy-efficient application assignment in profile-based data center management through a Repairing Genetic Algorithm	M Vasudevan, YC Tian, M Tang, E Kozan, X Zhang	2018	Elsevier
Joint minimization of the energy costs from computing, data transmission, and migrations in cloud data centers	C Canali, L Chiaraviglio, R Lancellotti, M Shojafar	2018	IEEE
Energy-efficient dynamic virtual machine management in data centers	Z Han, H Tan, R Wang, G Chen, Y Li, FCM Lau	2019	IEEE
An Apriori-based energy-efficient Algorithm for SDN data center	P HongYu, H TianLu	2019	IEEE
A Novel Approach to Adaptive Flow Scheduling for Energy Efficient Data Center Network	R Ranjana, S Radha, J Raja	2019	Journal of Internet Technology
CLOUD DATA CENTER BASED ENERGY EFFICIENT SCHEDULING OF SERVERS WITH MULTI-SLEEP MODES	PS JYOTHI, BH BABU	2019	Journal of Engineering Sciences
Short-term prediction model to maximize renewable energy usage in cloud data centers	A Khosravi, R Buyya	2018	Springer
Hybrid Best-Fit Heuristic for Energy Efficient Virtual Machine Placement in Cloud Data Centers	S Jangiti, V Vijayakumar, V Subramaniyaswamy	2020	EAI Endorsed Transactions on Energy Web
An SDN Focused Approach for Energy Aware Traffic Engineering in Data Centers	P Charalampou, ED Sykas	2019	Multidisciplinary Digital Publishing Institute
Exploiting user provided information in dynamic consolidation of virtual machines to minimize energy consumption of cloud data centers	MA Khan, AP Paplinski, AM Khan, M Murshed, R Buyya	2018	IEEE
DREAM: Distributed energy-aware traffic management for data center networks	L Zhou, LN Bhuyan, KK Ramakrishnan	2019	ACM
Energy-oriented analysis of HPC cluster queues: emerging metrics for sustainable data center	A Grishina, M Chinnici, D De Chiara, E Rondeau, AL Kor	2018	Springer
Energy efficiency of data center operating practices: Server clustering, powering on/off, and bang–bang control	Y Cho, YM Ko	2018	Wiley Online Library
Toward an Autonomic and Adaptive Load Management Strategy for Reducing Energy Consumption under Performance Constraints in Data Centers.	A Nahhas, S Bosse, M Pohl, K Turowski	2019	researchgate.net
Utilization-prediction-aware virtual machine consolidation approach for energy-efficient cloud data centers	SY Hsieh, CS Liu, R Buyya, AY Zomaya	2020	Elsevier
Reducing energy consumption in SDN-based data center networks through flow consolidation strategies	MS Conterato, TC Ferreto, F Rossi, WS Marques, PSS Souza	2019	ACM
An energy-saving strategy based on multi-server vacation queuing theory in cloud data center	Y Chunxia, J Shunfu	2018	Springer
Energy aware resource efficient-(eare) server consolidation framework for cloud datacenter	D Saxena, AK Singh	2020	Springer
ESP-VDCE: Energy, SLA, and price-driven virtual data center embedding	K Kaur, S Garg, G Kaddoum, S Guo	2020	IEEE
Virtual Machine Migration and Rack Consolidation for Energy Management in Cloud Data Centers	IG Hemanandhini, R Pavithra, P Sugantha Priyadharshini	2020	Springer
GreenPOD: Leveraging queuing networks for reducing energy consumption in data centers	F Balde, H Elbiaze, B Gueye	2018	IEEE
Optimization of energy consumption of green data center in e-commerce	Q Zhou, J Lou, Y Jiang	2019	Elsevier
Energy-aware dynamic resource management in elastic cloud datacenters	AA Khan, M Zakarya, R Khan	2019	Elsevier
EPBLA: energy-efficient consolidation of virtual machines using learning automata in cloud data centers	N Rasouli, R Razavi, HR Faragardi	2020	Springer
An Energy Saving-Oriented Incentive Mechanism in Colocation Data Centers	C Chi, K Ji, A Marahatta, F Zhang, Y Wang, Z Liu	2020	IEEE
Optimal Energy aware Dynamic Virtual Machine consolidation in Cloud Data Centers	KS Reddi, SK Pasupuleti	2019	IEEE
Stochastic Modeling and Performance Analysis of Energy-Aware Cloud Data Center Based on Dynamic Scalable Stochastic Petri Net	H He, Y Zhao, S Pang	2020	Computing and Informatics
An Energy-efficient Genetic-based Algorithm for Virtual Machine Placement in Cloud Datacenter	P Saeedi	2019	Journal of Multidisciplinary Engineering Science Studies
Location-aware energy efficient virtual network embedding in software-defined optical data center networks	Y Zong, Y Ou, A Hammad, K Kondepu, R Nejabati, D Simeonidou, Y Liu, L Guo	2018	Journal of Optical Communications and Networking
Energy-Efficient Resource Allocation Strategy Based on Task Classification in Data Center	H Li, S Ding, P Zhang, J Lai	2018	Atlantis Press
An adaptive autonomic framework for optimizing energy consumption in the cloud data centers	S Diouani, H Medromi	2019	International Journal of Intelligent Engineering & Systems
Minimizing SLA violation and power consumption in Cloud data centers using adaptive energy-aware algorithms	Z Zhou, J Abawajy, M Chowdhury, Z Hu, K Li, H Cheng, AA Alelaiwi, F Li	2018	Elsevier
Energy Optimization for Software-Defined Data Center Networks Based on Flow Allocation Strategies	Z Lu, J Lei, Y He, Z Li, S Deng, X Gao	2019	Multidisciplinary Digital Publishing Institute
A proposed energy and performance aware cloud framework for improving service level agreements (SLAs) in cloud datacenters	AAH Al-Mahruqi, V Athinarayanana…	2018	International Journal of Applied Engineering Research
A reliable energy-aware approach for dynamic virtual machine consolidation in cloud data centers	MH Sayadnavard, AT Haghighat…	2019	Springer
Memory-aware resource management algorithm for low-energy cloud data centers	B Liang, X Dong, Y Wang, X Zhang	2020	Elsevier
Improving the energy efficiency of virtual data centers in an IT service provider through proactive fuzzy rules-based multicriteria decision making	A Cocaña-Fernández, J Rodríguez-Soares…	2019	Springer
ETAS: Energy and thermal-aware dynamic virtual machine consolidation in cloud data center with proactive hotspot mitigation	S Ilager, K Ramamohanarao…	2019	Wiley Online Library
Energy efficient data center resources management using beam search algorithm	S Telenyk, O Rolik, E Zharikov…	2018	content.sciendo.com
Towards an optimized energy consumption of resources in cloud data centers	S Diouani, H Medromi	2018	Springer
Energy and service level agreement aware resource allocation heuristics for cloud data centers	K Sutha, GM Nawaz	2018	koreascience.or.kr
An energy-efficient algorithm for virtual machine placement optimization in cloud data centers	S Azizi, D Li	2020	Springer
DQN-based energy-efficient routing algorithm in software-defined data centers	Z Yao, Y Wang, X Qiu	2020	International Journal of Distributed Sensor Networks
Optimized Energy Cost and Carbon Emission-Aware Virtual Machine Allocation in Sustainable Data Centers	T Renugadevi, K Geetha, K Muthukumar, ZW Geem	2020	Multidisciplinary Digital Publishing Institute
Joint server and network energy saving in data centers for latency-sensitive applications	L Zhou, CH Chou, LN Bhuyan…	2018	IEEE

Erlang Based Server Selection Scheme Using Software Defined Networking in Datacenter for Energy Conservation	A Husen, I Raza, SA Hussain	2019	IEEE
Energy-and locality-efficient multi-job scheduling based on MapReduce for heterogeneous datacenter	L Chen, ZH Liu	2019	Springer
Magnetic: Multi-agent machine learning-based approach for energy efficient dynamic consolidation in data centers	K Haghshenas, A Pahlevan, M Zapater…	2019	IEEE
An energy-efficient VM placement method for cloud data centers using a hybrid genetic algorithm	MA Kaaouache, S Bouamama	2018	Journal of Systems and Information Technology
Joint optimization of energy saving and load balancing for data center networks based on software defined networks	Y He, Z Lu, J Lei, S Deng, X Gao	2020	Wiley Online Library
Managing energy, performance and cost in large scale heterogeneous datacenters using migrations	M Zakarya, L Gillam	2019	Elsevier
A big data-enabled consolidated framework for energy efficient software defined data centers in IoT setups	K Kaur, S Garg, G Kaddoum…	2019	IEEE
Type-aware virtual machine management for energy efficient cloud data centers	A Al-Dulaimy, W Itani, R Zantout, A Zekri	2018	Elsevier
A novel coalitional game-theoretic approach for energy-aware dynamic VM consolidation in heterogeneous cloud datacenters	X Xiao, Y Xia, F Zeng, W Zheng, X Sun, Q Peng…	2019	Springer
An Incentive Mechanism for Improving Energy Efficiency of Colocation Data Centers Based on Power Prediction	C Chi, K Ji, A Marahatta, F Zhang…	2020	IEEE
Resource scheduling for energy-efficient in cloud-computing data centers	S Xu, L Liu, L Cui, X Chang, H Li	2018	IEEE
Energy-Efficient Resource Provisioning using Adaptive Harmony Search Algorithm for Compute-Intensive Workloads with Load Balancing in Datacenters	T Renugadevi, K Geetha, K Muthukumar, ZW Geem	2020	Multidisciplinary Digital Publishing Institute
SLA-aware and energy-efficient VM consolidation in cloud data centers using robust linear regression prediction model	L Li, J Dong, D Zuo, J Wu	2019	IEEE
Performance & Energy Consumption Metrics Of A Data Center According To The Energy Consumption Models Cubic, Linear, Square And Square Root	C Saad-Eddine, B Younes	2019	IEEE
New six-phase on-line resource management process for energy and sla efficient consolidation in cloud data centers.	E Arianyan, H Taheri, S Sharifian…	2018	International Arab Journal of Information Technology
EnLoB: Energy and load balancing-driven container placement strategy for data centers	K Kaur, S Garg, G Kaddoum, F Gagnon…	2019	IEEE
Energy aware virtual machine scheduling in data centers	Y Qiu, C Jiang, Y Wang, D Ou, Y Li, J Wan	2019	Multidisciplinary Digital Publishing Institute
Energy-Efficient Resource Allocation in Data Centers Using a Hybrid Evolutionary Algorithm	VD Reddy, GR Gangadharan, G Rao…	2020	Springer
Energy efficient scheduling of servers with multi-sleep modes for cloud data center	C Gu, Z Li, H Huang, X Jia	2018	IEEE
Availability-aware and Energy-efficient Virtual Cluster Allocation Based on Multi-objective Optimization in Cloud Datacenters	X Liu, B Cheng, S Wang	2020	IEEE
Simultaneous application assignment and virtual machine placement via ant colony optimization for energy-efficient enterprise data centers	F Alharbi, YC Tian, M Tang, MH Ferdaus, WZ Zhang…	2020	Springer
Green IT scheduling for data center powered with renewable energy	L Grange, G Da Costa, P Stolf	2018	Elsevier
SLA-Aware and Energy-Efficient VM Consolidation in Cloud Data Centers Using Host State Binary Decision Tree Prediction Model	L Li, J Dong, D Zuo, Y Zhao, T Li	2019	jstage.jst.go.jp
Prediction Method of Energy Consumption Based on Multiple Energy-Related Features in Data Center	Y Liang, Z Hu	2019	IEEE
Energy-Saving Resource Allocation in Cloud Data Centers	MM Than, T Thein	2020	IEEE
Energy-Efficient Resource Allocation Technique Using Flower Pollination Algorithm for Cloud Datacenters	MJ Usman, AS Ismail, AY Gital, A Aliyu…	2018	Springer
Adaptive Multi-Threshold Energy-Aware Virtual Machine Consolidation in Cloud Data Center	Y Hu, D Ding, K Kang, T Li	2019	IEEE
Energy-efficient VM-placement in cloud data center	SK Mishra, D Puthal, B Sahoo, PP Jayaraman…	2018	Elsevier
Prediction-Based Joint Energy Optimization for Virtualized Data Centers	M Al-Tarazi, JM Chang	2020	ACM
Renewable energy-aware big data analytics in geo-distributed data centers with reinforcement learning	C Xu, K Wang, P Li, R Xia, S Guo…	2018	IEEE
Classification-based and energy-efficient dynamic task scheduling scheme for virtualized cloud data center	A Marahatta, S Pirbhulal, F Zhang…	2019	IEEE
Delayed Best-Fit Task Scheduling to Reduce Energy Consumption in Cloud Data Centers	Z Dong, W Zhuang…	2019	IEEE
Energy Efficiency MapReduce Job Scheduling of Shuffle and Reduce Phases in Data Center	J Wang, X Li, X Zhu	2018	Springer
MEnSuS: An efficient scheme for energy management with sustainability of cloud data centers in edge–cloud environment	GS Aujla, N Kumar	2018	Elsevier
Energy-aware virtual machines allocation by krill herd algorithm in cloud data centers	M Soltanshahi, R Asemi, N Shafiei	2019	Elsevier
Energy-Efficient Algorithm for Load Balancing and VMs Reassignment in Data Centers	N Djennane, R Aoudjit…	2018	IEEE
Efficient techniques for energy saving in data center networks	Z Chkirbene, A Gouissem, R Hadjidj, S Foufou…	2018	Elsevier
Slow Replica and Shared Protection: Energy-Efficient and Reliable Task Assignment in Cloud Data Centers	Y Fan, C Wang, W Wu, T Znati…	2019	IEEE
A novel scheduling approach to improve the energy efficiency in cloud computing data centers	JK Jeevitha, G Athisha	2020	Springer
An on-line virtual machine consolidation strategy for dual improvement in performance and energy conservation of server clusters in cloud data centers	W Lin, W Wu, L He	2019	IEEE
Joint Energy Optimization of Cooling Systems and Virtual Machine Consolidation in Data Centers	H Liu, WK Wong, S Ye…	2020	IEEE
Reinforcement learning based methodology for energy-efficient resource allocation in cloud data centers	T Thein, MM Myo, S Parvin, A Gawanmeh	2018	Elsevier
An integer linear programming model and adaptive genetic algorithm approach to minimize energy consumption of cloud computing data centers	H Ibrahim, RO Aburukba, K El-Fakih	2018	Elsevier
Embedding individualized machine learning prediction models for energy efficient VM consolidation within Cloud data centers	SM Moghaddam, M O'Sullivan, C Walker…	2020	Elsevier
Energy Efficient Cloud Data Center Using Dynamic Virtual Machine Consolidation Algorithm	C Thiam, F Thiam	2019	Springer
Bridging Server and Cooling: Toward Effective Energy Management in Data Centers	B Zhou, X Song, X Shi, Y Lu…	2019	IEEE

An Energy-Efficient Task Scheduling Mechanism with Switching On/Sleep Mode of Servers in Virtualized Cloud Data Centers	C Yin, J Liu, S Jin	2020	hindawi.com
Exact algorithms for energy-efficient virtual machine placement in data centers	C Wei, ZH Hu, YG Wang	2020	Elsevier
SLA-Aware and Energy-Efficient VM Consolidation in Cloud Data Centers Using Host States Naive Bayesian Prediction Model	L Li, J Dong, D Zuo, JI Liu	2018	IEEE
An empirical evaluation of energy-aware load balancing technique for cloud data center	NJ Kansal, I Chana	2018	Springer
Energy-aware virtual machine allocation and selection in cloud data centers	VD Reddy, GR Gangadharan, GSVRK Rao	2019	Springer
Energy-efficient and sla-aware virtual machine selection algorithm for dynamic resource allocation in cloud data centers	SM Moghaddam, SF Piraghaj, M OS'ullivan, C Walker, C Unsworth	2018	IEEE
EnLoc: Data locality-aware energy-efficient scheduling scheme for cloud data centers	K Kaur, N Kumar, S Garg, JJPC Rodrigues	2018	IEEE
Energy Efficient and Multi-Parameters Based VM Selection for Cloud Data Centers	S Singh, MS Aswal	2019	International Conference on Advances in Engineering Science Management & Technology
Energy-aware fault-tolerant dynamic task scheduling scheme for virtualized cloud data centers	A Marahatta, Y Wang, F Zhang, AK Sangaiah, SKS Tyagi, Z Liu	2019	Springer
An Energy Prediction Model for Cloud Data Centers Through Performance Counter.	S Meng, P Sun, J Luo, H Xu	2019	International Journal of Performability Engineering
A learning automata-based algorithm for energy and SLA efficient consolidation of virtual machines in cloud data centers	M Ranjbari, JA Torkestani	2018	Elsevier
Reallocation of Virtual Machines to Cloud Data Centers to Reduce Service Level Agreement Violation and Energy Consumption Using the FMT Method	HF Farimani, SRK Tabbakh, D Bahrepour, R Ghaemi	2019	Journal of Information Systems and Telecommunication
Energy Consumption of IT System in Cloud Data Center: Architecture, Factors and Prediction	H Lin, X Xu, X Wang	2019	Springer
Measurement, Analysis, and Enhancement of Multipath TCP Energy Efficiency for Datacenters	J Zhao, J Liu, H Wang, C Xu, W Gong, C Xu	2019	IEEE
LACE: A locust-inspired scheduling algorithm to reduce energy consumption in cloud datacenters	HA Kurdi, SM Alismail, MM Hassan	2018	IEEE
Virtual machine consolidation framework for energy and performance efficient cloud data centers	RA Arockia, S Arun	2019	IEEE
PEFS: AI-driven Prediction based Energy-aware Fault-tolerant Scheduling Scheme for Cloud Data Center	A Marahatta, Q Xin, C Chi, F Zhang, Z Liu	2020	IEEE
BiTE: a dynamic bi-level traffic engineering model for load balancing and energy efficiency in data center networks	N Rikhtegar, M Keshtgari, O Bushehrian, G Pujolle	2021	Springer
J-OPT: A Joint Host and Network Optimization Algorithm for Energy-Efficient Workflow Scheduling in Cloud Data Centers	A Jayanetti, R Buyya	2019	ACM
Energy performance of heuristics and meta-heuristics for real-time joint resource scaling and consolidation in virtualized networked data centers	M Scarpiniti, E Baccarelli, PGV Naranjo, A Uncini	2018	Springer
Energy consumption improvement and cost saving by cloud broker in cloud datacenters.	A Karamollahi, A Chalechale, M Ahmadi	2018	The International Arab Journal of Information Technology
Energy efficiency in virtual machines allocation for cloud data centers with lottery algorithm	M Tarahomi, M Izadi	2019	International Journal of Electrical and Computer Engineering
Energy-aware virtual data center embedding	X Ma, Z Zhang, S Su	2020	Journal of Information Processing Systems
Truthful Double Auction Based VM Allocation for Revenue-Energy Trade-Off in Cloud Data Centers	YS Patel, A Nighojkar, R Misra	2019	IEEE
Energy policies for data-center monolithic schedulers	D Fernández-Cerero, A Fernández-Montes, JA Ortega	2018	Elsevier
Greening cloud data centers in an economical way by energy trading with power grid	C Gu, L Fan, W Wu, H Huang, X Jia	2018	Elsevier
An Energy and SLA-Aware Resource Management Strategy in Cloud Data Centers	C Zhang, Y Wang, Y Lv, H Wu, H Guo	2019	Hindawi Scientific Programming
Ts-batpro: Improving energy efficiency in data centers by leveraging temporal–spatial batching	F Yao, J Wu, G Venkataramani, S Subramaniam	2018	IEEE
Intra-and Inter-Server Smart Task Scheduling for Profit and Energy Optimization of HPC Data Centers	SA Mamun, A Gilday, AK Singh, A Ganguly, GV Merrett, X Wang, BM Al-Hashimi	2020	Multidisciplinary Digital Publishing Institute
A demonstration of monitoring and measuring data centers for energy efficiency using open-source tools	J Gustafsson, S Fredriksson, M Nilsson-Mäki…	2018	ACM
Energy Efficient Scheduling Based on Marginal Cost and Task Grouping in Data Centers	K Ji, C Chi, A Marahatta, F Zhang, Z Liu	2020	ACM
Development and Application of Metrics for Evaluation of Cumulative Energy Efficiency for IT Devices in Data Centers	F Peñaherrera, K Szczepaniak	2019	Springer
Communication-Aware and Energy Saving Virtual Machine Allocation Algorithm in Data Center	J Luo, X Fan, L Yin	2019	IEEE
Genetic algorithm-based tabu search for optimal energy-aware allocation of data center resources	R Chandran, SR Kumar, N Gayathri	2020	Springer
Prediction-based underutilized and destination host selection approaches for energy-efficient dynamic VM consolidation in data centers	K Haghshenas, S Mohammadi	2020	Springer
A novel host readiness factor for energy-efficient VM consolidation in cloud data centers	S Ismaeel, A Miri, A Al-Khazraji	2019	IEEE
Smart deployment of virtual machines to reduce energy consumption of cloud computing based data centers using gray wolf optimizer	H Shahbazi, S Jamshidi-Nejad	2018	Springer
An ant colony system for energy-efficient dynamic virtual machine placement in data centers	F Alharbi, YC Tian, M Tang, WZ Zhang, C Peng, M Fei	2019	Elsevier
Holistic energy and failure aware workload scheduling in Cloud datacenters	X Li, X Jiang, P Garraghan, Z Wu	2018	Elsevier
EATSDCD: A green energy-aware scheduling algorithm for parallel task-based application using clustering, duplication and DVFS technique in cloud datacenters	B Barzegar, H Motameni, A Movaghar	2019	IOS Press Content Library
Energy proportionality in near-threshold computing servers and cloud data centers: Consolidating or Not?	A Pahlevan, YM Qureshi, M Zapater, A Bartolini, D Rossi, L Benini, D Atienza	2018	IEEE
Sharing with Live Migration Energy Optimization Scheduler for Cloud Computing Data Centers	S Alshathri, B Ghita, N Clarke	2018	Multidisciplinary Digital Publishing Institute
Energy-Aware Multi-Objective Placement of Virtual Machines in Cloud Data Centers	HA Al-shehri, K Hamdi	2018	ACM

A cloud data center virtual machine placement scheme based on energy optimization	S Zhang, F Meng, Z Zhang	2018	IEEE
An adaptive heuristic for managing energy consumption and overloaded hosts in a cloud data center	R Yadav, W Zhang, K Li, C Liu, M Shafiq, NK Karn	2018	Springer
Distributed Energy Management for Multiple Data Centers with Renewable Resources and Energy Storages	G Zhang, S Zhang, W Zhang, Z Shen, L Wang	2020	IEEE
An artificial neural network based approach for energy efficient task scheduling in cloud data centers	M Sharma, R Garg	2020	Elsevier
CSL-driven and energy-efficient resource scheduling in cloud data center	H Li, Y Zhao, S Fang	2020	Springer
Evaluating the upper bound of energy cost saving by proactive data center management	R Milocco, P Minet, E Renault, S Boumerdassi	2020	IEEE
A framework to optimize energy efficiency in data centers based on certified KPIs	V Gizli, J Marx Gómez	2018	Multidisciplinary Digital Publishing Institute
An Energy-Efficient Allocation Technique for Distributing Resources in a Heterogeneous Data Center	M Mursleen, Y Kothyari	2019	IEEE
An Energy Dynamic Control Algorithm Based on Reinforcement Learning for Data Centers	Y Xiang, J Yuan, R Luo, X Zhong, T Li	2019	International Journal of Pattern Recognition and Artificial Intelligence
Data center network energy consumption minimization: a hierarchical FAT-tree approach	J Mishra, J Sheetlani, KHK Reddy	2018	Springer
GREEN GEOGRAPHICALLY LOAD BALANCING USING VIABILITY OF DISTRIBUTED DATA CENTERS'LOCAL CONDITION FOR ENERGY EFFICIENCY	S TAHERI, M GOUDARZI	2019	Scientific Information Database
ENEDI: Energy Saving in Datacenters	A Tryfonos, A Andreou, N Loulloudes…	2018	IEEE
Thermal-aware hybrid workload management in a green datacenter towards renewable energy utilization	Y Li, X Wang, P Luo, Q Pan	2019	Multidisciplinary Digital Publishing Institute
Energy-efficient virtual content distribution network provisioning in cloud-based data centers	D Liao, G Sun, G Yang, V Chang	2018	Elsevier
A virtualized data center energy-saving mechanism based on switching operating mode of physical servers and reserving virtual machines	C Yin, J Liu, S Jin	2020	Wiley Online Library
Energy-aware Fault-tolerant Scheduling Scheme based on Intelligent Prediction Model for Cloud Data Center	A Marahatta, C Chi, F Zhang, Z Liu	2018	IEEE
Multilevel resource allocation for performance-aware energy-efficient cloud data centers	FD Rossi, PSS de Souza, W dos Santos Marques, M da Silva Conterato, TC Ferreto, AF Lorenzon, MC Luizelli	2019	IEEE
Sampling Workloads with Dynamic Time Scale to Promote the Energy Efficiency of Datacenters	C Hu, Y Zhou, R Ding	2020	IEEE
Interval graph multi-coloring-based resource reservation for energy-efficient containerized cloud data centers	YS Patel, A Baheti, R Misra	2020	Springer
Modeling Energy Efficiency of Future Green Data centers	T Bhattacharya, X Qin	2020	IEEE
A system of systems approach for data centers optimization and integration into smart energy grids	M Antal, C Pop, T Cioara, I Anghel, I Salomie…	2020	Elsevier
Improving big data centers energy efficiency: Traffic based model and method	G Kuchuk, A Kovalenko, IE Komari, A Svyrydov…	2019	Springer
Data Center Server Energy Consumption Optimization Algorithm	I Stamatescu, S Ploix, I Făgărăşan…	2018	IEEE
An efficient energy-aware method for virtual machine placement in cloud data centers using the cultural algorithm	M Mohammadhosseini, AT Haghighat, E Mahdipour	2019	Springer
Datazero: Datacenter with zero emission and robust management using renewable energy	JM Pierson, G Baudic, S Caux, B Celik, G Da Costa, L Grange, M Haddad, J Lecuivre, JM Nicod, L Phillipe. V Rehn-Sonigo, R Roche, G Rostirolla, A Sayah, P Stolf, MT Thi, C Varnier	2019	IEEE
Energy-Efficient Data Center Networks	JA Manjate, M Hidell, P Sjödin	2018	IEEE
EcoVMbroker: energy-aware scheduling for multi-layer datacenters	R Fernandes, J Simão, L Veiga	2018	ACM
Energy-Efficient Workflow Scheduling using Container based Virtualization in Software Defined Data Centers	R Ranjan, I Thakur, GS Aujla, N Kumar, AY Zomaya	2020	IEEE
Energy-aware resource management framework for overbooked cloud data centers with SLA assurance	S Alanazi, B Hamdaoui	2018	IEEE
Segment routing based energy aware routing for software defined data center	B Balakiruthiga, P Deepalakshmi, SN Mohanty, D Gupta, PP Kuman, K Shankar	2020	Elsevier
Monte carlo based server consolidation for energy efficient cloud data centers	B Harris, N Altiparmak	2019	IEEE
A novel energy-aware resource management technique using joint VM and container consolidation approach for green computing in cloud data centers	N Gholipour, E Arianyan, R Buyya	2020	Elsevier
The Potential Influence of Workload Management Across Heterogeneous Server Systems on Datacenter Energy Use and Power Draw	DH Harryvan, R Chamberlane, A SCionti, G Urlini, O Terzo	2018	IEEE
Energy efficient VM scheduling strategies for HPC workloads in cloud data centers	AA Chandio, N Tziritas, MS Chandio, CZ Xu	2019	Elsevier
An energy, performance efficient resource consolidation scheme for heterogeneous cloud datacenters	AA Khan, M Zakarya, R Khan, IU Rahman…	2020	Elsevier
HIGA: Harmony-inspired genetic algorithm for rack-aware energy-efficient task scheduling in cloud data centers	M Sharma, R Garg	2020	Elsevier
MULTI-LEVEL ATTRIBUTE-BASED MATCHING APPROACH TOWARDS ENERGY-EFFICIENT RESOURCE PROVISIONING IN CLOUD DATA CENTERS.	F ELIJORDE, S KIM, J LEE	2018	Journal of Theoretical and Applied Information Technology
A green energy-efficient scheduler for cloud data centers	M Amoon, TEE Tobely	2019	Springer
Energy-Efficient Virtual Machine Replication for Data Centers	O Raluca, P Florin	2018	IEEE
Profile-based power-aware workflow scheduling framework for energy-efficient data centers	B Qureshi	2019	Elsevier
Performance-aware energy saving for data center networks	M Al-Tarazi, JM Chang	2019	IEEE
Energy-aware dynamic virtual machine consolidation for cloud datacenters	H Wang, H Tianfield	2018	IEEE
An energy-efficient strategy for virtual machine allocation over cloud data centers	X Qie, S Jin, W Yue	2019	Springer
Optimal energy-efficient policies for data centers through sensitivity-based optimization	JY Ma, L Xia, QL Li	2019	Springer