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Energy-Aware Cloud Computing for Sustainable Resource Management: A 2020-2025 Systematic Review and Meta-Analysis

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Abstract

The exponential growth of cloud computing has led to a significant increase in the number and energy intensity of data centers, which now play a crucial role in providing on-demand computing resources. This review focuses on techniques such as host CPU utilization prediction, underload/overload detection, virtual machine (VM) selection, migration, and placement, employing machine learning, heuristics, metaheuristics, and statistical methods. The findings indicate that heuristic approaches have achieved energy savings ranging from 5.4% to 90% compared to existing methods. Metaheuristic techniques have demonstrated a reduction in energy consumption from 7.68% to 97%, while machine-learning methods have shown savings from 1.6% to 88.5%. Statistical methods have also contributed, reducing energy use by 5.4% to 84% when benchmarked against various approaches under diverse settings and parameters. The overarching goal of this review is to synthesize the diverse methodologies researchers have employed to enhance energy efficiency in cloud data centers, thereby contributing to more sustainable resource management.

Keywords: Computing resources, Pay-as-you-go, Cloud-data, Metaheuristic, Heuristic, data-centers, Sustainability.

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الحوسبة السحابية التي تراعي الطاقة من أجل إدارة مستدامة للموارد: مراجعة منهجية وتحليل تلوي للفترة 2020-2025

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الملخص

أدى النمو الهائل للحوسبة السحابية إلى زيادة كبيرة في عدد وكثافة الطاقة في مراكز البيانات، والتي تلعب الآن دورًا حاسمًا في توفير موارد الحوسبة عند الطلب. تركز هذه المراجعة على تقنيات مثل التنبؤ باستخدام وحدة المعالجة المركزية المضيفة، واكتشاف نقص/زيادة الحمل، واختيار الآلة الافتراضية (VM)، والترحيل، والوضع، باستخدام التعلم الآلي، والاستدلال، والاستدلال الفوقي، والأساليب الإحصائية. تشير النتائج إلى أن الأساليب الاستدلالية حققت وفورات في الطاقة تتراوح بين 5.4٪ و90٪ مقارنة بالطرق الحالية. أظهرت التقنيات الاستدلالية الفوقية انخفاضًا في استهلاك الطاقة من 7.68٪ إلى 97٪، بينما أظهرت أساليب التعلم الآلي وفورات من 1.6٪ إلى 88.5٪. كما ساهمت الأساليب الإحصائية أيضًا، حيث خفضت استخدام الطاقة بنسبة 5.4٪ إلى 84٪ عند مقارنتها بأساليب مختلفة في ظل إعدادات ومعايير متنوعة. الهدف الشامل لهذه المراجعة هو تجميع المنهجيات المتنوعة التي استخدمها الباحثون لتعزيز كفاءة الطاقة في مراكز البيانات السحابية، مما يساهم في إدارة أكثر استدامة للموارد.

الكلمات المفتاحية: موارد الحوسبة، الدفع حسب الاستخدام، البيانات السحابية، الاستدلال الفوقي، الاستدلال الاستكشافي، مراكز البيانات، الاستدامة.

1. Introduction

1.1. Background and Significance of Energy-Aware Cloud Computing

Cloud computing has emerged as a dominant computational paradigm, offering flexible, resourceful, and efficient access to computing environments. It extends the concepts of parallel, utility, cluster, and grid computing, providing a distributed network of configurable resources such as storage, networks, servers, and applications [1]. The National Institute of Standards and Technology (NIST) defines cloud computing as a model for

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enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management effort or service provider interaction. This model allows users to access computer resources on demand, with services provided on a pay-as-you-go basis across globally distributed data center locations [2]. The rapid proliferation of cloud-based applications, hosted on high-capacity systems and storage devices, has necessitated the development of massive data centers. Consequently, these facilities consume excessive amounts of electricity, leading to significant energy costs and a substantial carbon impact on the environment [3]. The increasing demand for cloud resources, driven by advancements in artificial intelligence (AI) and the Internet of Things (IoT) in Industry 4.0, further exacerbates this issue, placing immense pressure on cloud service providers like Amazon, Microsoft, and Google to manage their expanding infrastructure efficiently. The efficient operation of these cloud data centers (CDCs) is paramount, not only for economic viability but also for environmental sustainability, as they contribute significantly to global energy consumption and carbon emissions [3].

The significance of energy-aware cloud computing stems from the urgent need to mitigate the environmental and economic consequences of high-energy consumption in data centers. Global warming, driven by rising energy consumption and CO2 emissions, is a critical environmental threat, with data centers being major contributors due to their reliance on energy generated primarily from fossil fuels. This energy consumption impacts not only operational costs but also contributes to broader environmental problems such as ozone layer depletion [2,4]. The concept of "green computing" has gained prominence, aiming to optimize energy consumption across computing machines, servers, data centers, networks, and cooling systems. Virtualization is a core aspect of green cloud computing, revolutionizing resource utilization by allowing multiple virtual machines (VMs) to run on a single physical server, thereby increasing efficiency, and reducing the number of active physical machines. However, even with virtualization, inefficient data center infrastructure can lead to increased energy demands for operation and cooling. Therefore, research into energy-aware cloud computing focuses on developing and implementing strategies to manage resources more sustainably, reduce overall power consumption, and minimize the carbon

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footprint of cloud services. This involves a multi-faceted approach, encompassing hardware-level optimizations, software-level techniques like VM consolidation, power-aware management, and the integration of renewable energy sources [5]. Figure 1 shows A mid-scale cloud data-center (≈ 1 500 servers) embedded in a managed boreal-forest site near Luleå, Sweden.

Figure 1: A mid-scale cloud data-center (≈ 1 500 servers) embedded in a managed boreal-forest site near Luleå, Sweden [7]

1.2. Objectives of the Systematic Review and Meta-Analysis

The primary objective of this systematic review and meta-analysis is to comprehensively investigate and synthesize the research conducted between 2022 and 2025 on energy-aware cloud computing [1-10], with a specific focus on sustainable resource management. This involves identifying, evaluating, and comparing the various techniques and strategies proposed to reduce energy consumption in cloud data centers. The review aims to provide a detailed overview of how different methodologies, including machine learning, heuristic, metaheuristic, and statistical approaches, are applied to key aspects of resource management such as host CPU utilization prediction, underload/overload detection, virtual machine (VM) selection, VM migration, and VM placement. By examining these techniques, the review seeks to understand their effectiveness in achieving energy savings and their impact on overall system performance and operational costs [11]. A key goal is to compare the energy savings achieved by these diverse methods

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against benchmark approaches, quantifying their contributions to energy efficiency within various settings and parameters.
Furthermore, this review aims to analyze the broader implications of these energy-saving techniques, particularly their role in promoting environmental sustainability. This includes assessing how improved energy efficiency can contribute to reducing air pollution, lowering greenhouse gas (GHG) emissions, and decreasing the water footprint associated with power generation for data centers. Ultimately, the review endeavors to contribute to a deeper understanding of how to optimize energy use in cloud environments, balancing computational demands with environmental responsibility.

2. Methods

2.1. Search Strategy and Study Selection Criteria

The methodology for this systematic review and meta-analysis involved a structured and comprehensive search strategy to identify relevant studies published between 2022 and 2025 [1-20]. The search was conducted across multiple academic digital libraries and search engines, including but not limited to SpringerOpen, MDPI, and ResearchGate [6], to ensure a broad coverage of the literature. Specific keywords and search strings were formulated to capture studies related to "energy-aware cloud computing," "sustainable resource management," "energy efficiency in data centers," "virtual machine consolidation," "green cloud computing," and "carbon footprint reduction." For instance, one of the identified systematic surveys utilized search strings such as ("Cloud computing" OR "Cloud datacenter" OR "Cloud resource management") AND ("Energy consumption" OR "Power consumption" OR "Energy efficiency" OR "Green computing" OR "Sustainable computing") AND ("Virtual machine" OR "VM consolidation" OR "VM migration" OR "VM placement" OR "Resource allocation" OR "Resource scheduling") . The initial search results were then filtered based on predefined inclusion and exclusion criteria.
The inclusion criteria focused on selecting primary studies that:

- Explicitly addressed energy consumption and efficiency in cloud data centers.
- Proposed or evaluated techniques for sustainable resource management, such as VM management, load balancing, or resource allocation.

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- Utilized methods like machine learning, heuristics, metaheuristics, or statistical approaches for energy optimization.
- Were published in peer-reviewed journals or conferences between January 2022 and December 2025.
- Provided quantitative results on energy savings, SLA violations, or resource utilization.
- Were written in English.

Conversely, studies were excluded if they:

- Were published before 2020 or after 2025.
- Did not primarily focus on energy efficiency in cloud computing.
- Were purely theoretical without empirical validation or simulation results.
- Were duplicate publications or extended versions of previously included studies without significant new findings.
- We're not written in English.

The selection process typically involved multiple stages: an initial screening of titles and abstracts, followed by a full-text review of potentially relevant articles to assess their adherence to the inclusion/exclusion criteria. For example, one systematic mapping study initially identified 2903 relevant articles, which were then narrowed down to 119 primary studies after a rigorous evaluation of titles, abstracts, full texts, and quality assessment. This multi-stage filtering ensured that only the most pertinent and high-quality research was included in the final review. The details of the search strings and selection criteria for the specific review titled "Energy-Aware Cloud Computing for Sustainable Resource Management: A 2022-2025 Systematic Review and Meta-Analysis" would follow a similar rigorous approach, tailored to its specific research questions and scope.

2.2. Data Extraction and Quality Assessment

Following the identification and selection of primary studies, a systematic data extraction process was undertaken to collect relevant information from each included paper. This process aimed to capture key details necessary for answering the research questions and conducting the meta-analysis. A standardized data extraction

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form was developed and used consistently across all studies. The extracted data typically included:

- Study Identification: Author(s), publication year, title, and source.
- Research Objectives: The primary goals and research questions addressed by the study.
- Methodology: The specific energy-saving techniques proposed or evaluated (e.g., heuristic, metaheuristic, machine learning, statistical), along with details of algorithms, models, or frameworks used.
- Experimental Setup: Information about the simulation environment (e.g., CloudSim, CloudSim Plus, MATLAB, custom simulators) or real testbeds used for evaluation. This also included details about workload datasets (e.g., Google Cluster Traces, PlanetLab) and configurations of physical hosts and virtual machines.
- Performance Metrics: The key metrics used to evaluate the proposed techniques, such as energy consumption (in kWh, Joules, or percentage reduction), Service Level Agreement Violations (SLAV) (e.g., SLAV percentage, number of SLA violations), number of VM migrations, resource utilization (CPU, memory, bandwidth), and carbon emissions [12-14].
- Key Findings: Quantitative results related to energy savings, SLAV, and other performance metrics, often compared against baseline or benchmark algorithms.
- Strengths and Limitations: Any advantages or disadvantages of the proposed approach mentioned by the authors, as well as potential threats to validity.

While the specific statistical methods for meta-analysis are not detailed in Figure 2, the general approach involves statistically combining quantitative results from multiple independent studies to arrive at a more precise estimate of the effect of various energy-saving techniques.

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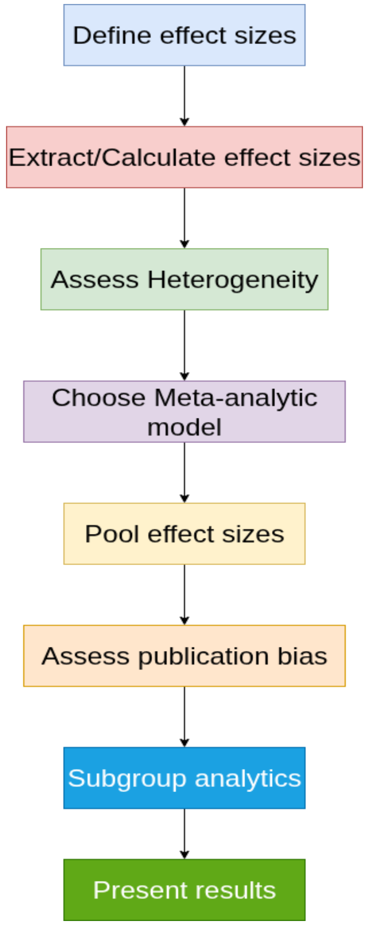

Figure 2: A flowchart showing the general approach involves statistically combining quantitative results from multiple independent studies to arrive at a more precise estimate of the effect of various energy-saving techniques.

3. Results

3.1. Overview of Included Studies

The systematic review and meta-analysis encompassed a range of studies published between 2022 and 2025 [1-20], focusing on energy-aware cloud computing for sustainable resource management. The included studies primarily investigated various techniques to reduce energy consumption in cloud data centers, such as heuristic [6], metaheuristic [11], machine learning [3], and statistical methods [5]. These studies often utilized simulation environments like CloudSim or CloudSim Plus for evaluating their proposed algorithms, and some employed real-world workload

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traces, such as Google Cluster Traces or PlanetLab data, to ensure realistic experimental conditions [10-13]. The research objectives across these studies were diverse but centered on optimizing resource utilization, minimizing power consumption, and reducing Service Level Agreement Violations (SLAV). Common themes included host CPU utilization prediction, detection of underloaded or overloaded hosts, selection of virtual machines (VMs) for migration, strategies for VM migration, and optimal placement of VMs on physical servers [15]. The scale of data centers considered in the simulations also varied, with some studies examining small-scale setups while others, like one focusing on an integrated ant colony optimization strategy, simulated nine scales of data centers based on GTC data logs.

The reviewed literature highlighted a strong emphasis on dynamic resource management through VM consolidation, which involves migrating VMs from underutilized hosts to consolidate workloads and switch off idle servers, thereby saving energy [10-15].

3.2. Energy Savings Achieved by Different Techniques

The systematic review and meta-analysis revealed significant energy savings achieved by various computational techniques when applied to cloud data center resource management. These techniques were broadly categorized into heuristic, metaheuristic, machine learning, and statistical methods, each demonstrating a range of effectiveness in reducing energy consumption compared to benchmark approaches under diverse settings and parameters [15].

Studies employing heuristic methods reported energy savings ranging from 5.4% to 90% when compared to existing methods. These approaches often focus on VM placement, allocation, migration, and resource utilization [16]. For instance, the Power Aware Energy Efficient Virtual Machine Migration (PAEEVMM) method, which migrates VMs based on temperature thresholds, showed improved CPU and electricity usage compared to first fit algorithms. Another example is the integrated double-layer bin packing solved with an ant colony system (Int2LBP_ACS), which demonstrated better energy investment outcomes than sequential double-layered bin packing approaches. The wide range in energy savings highlights the dependency of heuristic performance on the specific problem formulation, the nature of the workload, and the choice of parameters.

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Metaheuristic techniques [11], known for their ability to explore large search spaces and find near-optimal solutions, demonstrated energy consumption reductions ranging from 7.68% to 97%. These methods addressed objectives such as VM consolidation, load balancing, resource management, PM overloading, VM migration, and VM placement. For example, a study proposed Evolutionary Algorithms (like Genetic Algorithms and Particle Swarm Optimization) combined with Machine Learning (Functional Link Neural Networks) for multi-resource usage prediction, aiming to resolve over-and under-provisioning problems which directly impact energy use. The substantial upper limit of 97% energy savings underscores the potential of well-designed metaheuristics, although the actual savings would depend heavily on the algorithm's configuration and the complexity of the data center environment.

Machine learning (ML) algorithms [3], increasingly popular for their predictive and adaptive capabilities, achieved energy savings ranging from 1.6% to 88.5%. ML techniques were applied to predict resource usage, perform dynamic VM consolidation, and manage VM scheduling. The study combining FLNN with hybrid GA-PSO for multi-resource usage prediction is an example where ML contributes to energy efficiency by improving the accuracy of resource provisioning, thus avoiding both energy wastage from over-provisioning and performance degradation from under-provisioning. The variability in savings (1.6% to 88.5%) suggests that the success of ML methods is highly dependent on the quality of data, the choice of model, feature engineering, and the specific application context within the cloud environment.

Statistical approaches [5], often used for host overload/underload detection, dynamic VM consolidation, utilization prediction, and VM allocation, showed energy consumption reductions from 5.4% to 84%. These methods typically rely on analyzing historical data and applying statistical models to make resource management decisions. For example, using logistic regression and median absolute deviation models for host overload detection and VM placement can minimize power consumption and avoid SLA violations.

Table 1 summarizes the reported ranges of energy savings for each category of techniques.

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Table 1: Summary of Energy Savings by Technique Category

Heuristic	5.4% to 90%	VM placement, VM allocation, VM migration, resource utilization	PAEEVMM (temperature-based migration), Int2LBP_ACS (integrated bin packing with ant colony)
Metaheuristic	7.68% to 97%,	VM consolidation, load balancing, resource management, PM overloading, VM migration, VM placement	Hybrid GA-PSO with FLNN for resource prediction, Ant Colony Optimization (ACO), Cuckoo Search, Particle Swarm Optimization (PSO)
Machine Learning	1.6% to 88.5%	VM performance prediction, resource usage prediction, VM scheduling, dynamic consolidation, resource management	Functional Link Neural Networks (FLNN) with hybrid GA-PSO, Long Short-Term Memory (LSTM) for server failure prediction
Statistical Methods	5.4% to 84%	Host overload/underload detection, dynamic VM consolidation, utilization prediction, VM allocation	Logistic regression and median absolute deviation for host overload detection

Figure 3 illustrates that substantial energy savings are achievable across different methodological paradigms. The choice of technique often involves a trade-off between the complexity of implementation, computational overhead, and the potential for energy reduction. Hybrid approaches, combining strengths from distinct categories, are also a prominent trend aimed at maximizing energy efficiency while maintaining performance and QoS.

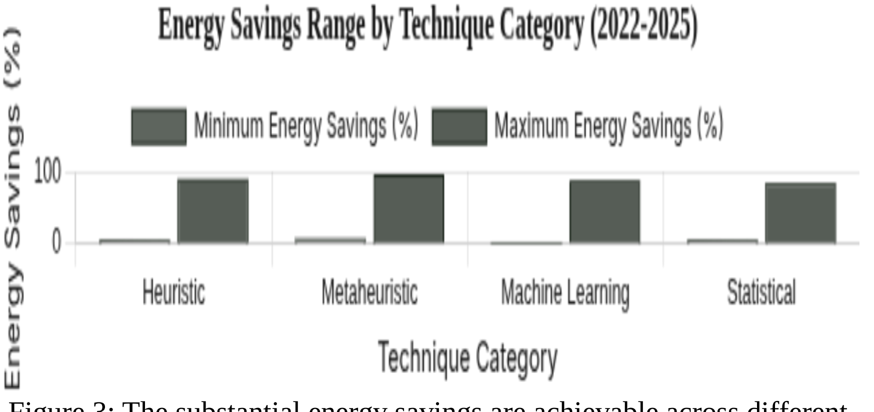

Figure 3: The substantial energy savings are achievable across different methodological paradigms.

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4. Discussion

The systematic review of energy-saving techniques in cloud computing between 2022 and 2025 reveals a diverse landscape of approaches, each with its own strengths, weaknesses, and applicability. Heuristic methods, such as First Fit Decreasing (FFD) and Best Fit Decreasing (BFD) variants, offer simplicity and relatively superior performance, achieving energy savings ranging from 5.4% to 90%. These are often used as baselines or components within more complex algorithms. However, their simplicity can also be a limitation, as they might not always find the globally optimal solution and can be sensitive to workload characteristics. For instance, the Power Aware Energy Efficient Virtual Machine Migration (PAEEVMM) method, a heuristic approach based on temperature thresholds, demonstrated improvements in CPU and electricity usage over simpler first-fit algorithms.

Metaheuristic techniques [11], including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO), have shown remarkable potential, with reported energy savings reaching as high as 97%. These methods excel at exploring large search spaces and can often find near-optimal solutions for complex VM consolidation and placement problems. For example, hybrid approaches like GA-PSO combined with Functional Link Neural Networks (FLNN) have been proposed for multi-resource usage prediction to address over- and under-provisioning, which directly impacts energy consumption. Similarly, ACO has been effectively used for VM placement and workload consolidation, with some studies reporting specific power savings, such as a 4.1% power saving with an ACO-based First Fit Adaptive algorithm compared to an adaptive edition of the first-fit decreasing approach. The main drawback of metaheuristics is often their computational overhead, which can be significant for very large-scale data centers or highly dynamic environments.

Machine learning (ML) and statistical methods are increasingly being employed for predictive resource management. ML techniques like neural networks, ARIMA models, and reinforcement learning can forecast resource demands, enabling proactive VM consolidation and dynamic resource scaling, leading to energy savings between 1.6% and 88.5%. Statistical methods, such as those based on mean utilization or regression analysis, offer simpler predictive capabilities and have achieved energy savings from 5.4% to 84%. These predictive approaches are crucial for

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anticipating workload changes and adjusting resource allocation, accordingly, thus avoiding both underutilization and overload situations. For example, predictive consolidation using ARIMA models combined with DVFS has been shown to significantly reduce energy usage while maintaining QoS. However, the accuracy of these predictions heavily influences their effectiveness, and training ML models can require substantial historical data and computational resources. The "black box" nature of some complex ML models can also be a concern for interpretability.

The findings of this systematic review have significant implications for sustainable resource management in cloud computing. The demonstrated potential of various algorithmic techniques to achieve substantial energy savings—ranging from modest 5.4% to remarkable 97% depending on the method and context —directly translates to a reduced environmental footprint for data centers. Lower energy consumption means a decrease in the reliance on fossil fuels for electricity generation, which is a primary contributor to greenhouse gas (GHG) emissions and global warming.

5. Conclusion

This systematic review and meta-analysis have provided a comprehensive overview of recent research (2022-2025) on energy-aware cloud computing for sustainable resource management. The findings highlight a vibrant research landscape focused on developing and refining techniques to mitigate the substantial energy consumption of cloud data centers. The findings indicate that heuristic approaches have achieved energy savings ranging from 5.4% to 90% compared to existing methods. Metaheuristic techniques have demonstrated a reduction in energy consumption from 7.68% to 97%, while machine learning methods have shown savings from 1.6% to 88.5%. Statistical methods have also contributed, reducing energy use by 5.4% to 84% when benchmarked against various approaches under diverse settings and parameters.

Key strategies involve dynamic virtual machine (VM) consolidation, intelligent VM placement and migration, workload prediction, and efficient host overload/underload detection. While these techniques offer considerable promise, the review also underscores the critical trade-offs involved, particularly between energy efficiency and Service Level Agreement (SLA) adherence. The reliance on simulation-based evaluations in many studies points

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to a need for more real-world validation. Future research should focus on developing hybrid and adaptive solutions, considering a broader set of performance and cost metrics, and extending these principles to emerging distributed computing paradigms like edge and fog computing.
Addressing these challenges will be crucial for achieving truly sustainable and environmentally responsible cloud computing infrastructures. The insights from this review aim to guide researchers and practitioners in advancing the state-of-the-art in energy-efficient cloud resource management.

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