Optimization of power consumption in data centers using machine learning based approaches: a review

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Article Info

Article history:

Received Jun 5, 2021
Revised Sep 26, 2021
Accepted Oct 12, 2021

Keywords:

Data center
Decision-making
Machine learning
Optimization
Power usage

ABSTRACT

Data center hosting is in higher demand to fulfill the computing and storage requirements of information technology (IT) and cloud services platforms which need more electricity to power on the IT devices and for data center cooling requirements. Because of the increased demand for data center facilities, optimizing power usage and ensuring that data center energy quality is not compromised has become a difficult task. As a result, various machine learning-based optimization approaches for enhancing overall power effectiveness have been outlined. This paper aims to identify and analyze the key ongoing research made between 2015 and 2021 to evaluate the types of approaches being used by researchers in data center energy consumption optimization using Machine Learning algorithms. It is discussed how machine learning can be used to optimize data center power. A potential future scope is proposed based on the findings of this review by combining a mixture of bioinspired optimization and neural network.

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1. INTRODUCTION

The major reason for varying emissions on earth is due to human activity. As the atmospheric temperature increases above the normal surface temperature, it leads to global warming [1]. Greenhouse gas emissions are the predominant anthropogenic source of global warming. Various greenhouse gases include hydrofluorocarbons, carbon dioxide, ozone, nitrous oxides, and methane. Industrial activities, animal waste, and data centers are some of the primary sources of greenhouse gas emissions [2]. The information technology (IT) sector accounts for around 2% of greenhouse gas emissions, with data centers accounting for the majority of these [3]. Green computing refers to the current development of such industries in the environmentally sustainable usage and output of computers and other computing-related equipment [4]. The data centers are going green with a green computational method for reducing the amount of energy used by data centers [5]. In the context of green computing, data center facilities should be designed to use as few resources as possible. Cooling machines, for example, computers, electrical backup systems, network equipment and eco-friendly storage must be built.

This large-scale management of data has contributed to increased use of energy. There are close to around 500 huge data centers, which are thought to account for around 3% of total energy consumption [6]. The United States accounts for about half of these data centers, while western Europe and eastern Asia contributes to a significant amount [7]. Thanks to the broad variety of technological upgrades, the data stored in cloud that is contributing to big data is rising rapidly. As per the customer's need the service providers provide customized cloud services with lesser downtime. This growth in the quantity of data centers has led to challenging issues with power storage and energy quality concerns. The growth in the cost of electricity and other issues from environmentalists are forcing the data centers to boost their operational performance. Estimating a data center's energy usage is critical for management to understand which operations consume the most energy and to take steps to reduce overall power usage. This can be significantly decreased by introducing a smart work process. The energy consumption of a gadget that collects data center IT infrastructure is investigated in this study. To describe an energy prediction model, the user must first comprehend how energy is spent by the server's various components [8].

Various machine learning techniques have been discussed for articulating data center power management with intelligent decision-making in IT management [9]. The cooling process in a data center is crucial since several computers working close to generate a lot of heat, and high temperatures will reduce IT output or possibly injure equipment. Significant advancements in cooling performance have been made, and effective recommendations are now used in larger data centers. Power management is essential in data centers because it ensures that computer services are properly deployed to meet customer requirements while retaining the quality of service (QoS) intensities based on service level agreements (SLA). Since many virtual machines are co-located on the same nodes, performance is hampered by the need for cost savings by restructuring. To prevent such problems, existing vendors take a measured approach to resource management, which results in severe underutilization [10].

As contributions, this work has reviewed the literature related to data center power optimization from 2015 to 2021. This would help in identifying the limitations in the existing literature and make recommendations to reduce energy consumption. The paper's structure is organized around seven sections. This section briefs the basic introduction about power consumption in data centers. Section 2 explains the related studies using machine learning techniques. Section 3 explains the combined study for the background research for the paper. Section 4 explains how various factors such as cooling systems, resource management, and power management influence the energy efficiency of data centers section 5 describes a group of studies that use machine learning methods to solve a problem. Section 6 synthesizes the main challenges in the existing system, gaps, and the considered recommendations. Finally, the key points about power optimization using machine learning techniques will be discussed, including synthesis and future work.

2. RELATED STUDIES USING MACHINE LEARNING TECHNIQUES

Bahari and Shariff [1] have illustrated the substantial rise in energy use in data centers with the increase in energy demand. It's been suggested that a green data center has been developed, which uses green computing to minimize energy consumption. Green computation requires computing the resource efficiency and processing performance of the device. The analysis indicates that data center (DC) electricity usage is rising by around 1.5% annually. If this occurs, so energy prices are likely to rise as well. Backup power storage must be improved to boost device stability, which reduces data center energy efficiency. Upgrades to modules that are seldom used in data centers may improve the energy efficiency of the device. When maintaining the required performance at the target level, it is important to reduce energy consumption. It has been studied that the data centers have issues like throughput, reduced efficiency, and failure of equipment. Therefore, green data centers have been suggested as an alternative to improve the system.

Several power issues in data centers have been pointed out by Azimzadeh and Tabrizi [11]. Computer devices have challenges such as higher electricity use, emissions, construction materials, and high expenditure. The research has suggested the usage of excess heat from IT machinery and the evaporative cooling system are adequate to support the straight, refreshing air structure. The two proposals to reduce energy consumption on servers include dynamic voltage frequency scaling and dynamic power control strategies. The MapReduce optimization strategy will help to reduce energy consumption significantly. Scheduling algorithm has been suggested for effective power optimization.

Deep reinforcement learning (DRL) has demonstrated its strength in a lot of ways for fields as the research and implementations have flourished [12]. In Q-learning, the deep Q-network (DQN) proposed uses a neural network approximation. Subsequent DQN research has focused on strengthening the system's teaching stability and expanding the framework to address issues with continuous control variables. Deep reinforcement learning has been proposed for use in a variety of technologies, including video editing and text-based games. However, DRL has not been validated in a realistic control device, such as a DC cooling system, high simulation costs can be a problem, and the reliability criterion is high.

Xia *et al.* [13] have discussed about the technological options as well as the economic opportunity to balance the power system as the power grid absorbs a growing amount of distributed generation. The embedded systems are suggested as sensors for a novel real-time power analytics architecture to track the power consumption in a fine-grained, real-time manner. This comprehensive management and optimization framework have reduced the total resource usage of the data center and also allows for time shifting of processes in the data center caused by the incorporation of distributed generation into the power grid. In the paper, Li *et al*. [14] has proposed a method for systemic power prediction model. Various power series models are analyzed to explain the repeated patterns. Then an approach to remove the noise that reduces noise intrusion to the modelling is performed. A recursive autoencoder (AE) is utilized for shorter term prediction and the findings show that the proposed models outperform traditional prediction methods in terms of accuracy, with up to a 79% reduction in error in some cases. However, the obtained precision is extremely poor.

Zheng *et al.* [15] has proposed a server and cooling coordinating power optimization environment known as PowerNetS for minimizing data center power consumption. The model uses workload similarity analysis to increase energy efficiency when consolidating server and traffic. Most importantly, by decreasing the quantity of switches, more intra-node traffic and shorter flows can be accomplished. The model was tested on a physical testbed that had ten virtual switches and six servers installed via the 48-port development switch OpenFlow. PowerNetS is seen to have saved up to 14.6% electricity by working more with the ventilation to use different cooling efficiencies at various places in the data centers.

Scheduling has also been proposed by Hu *et al*. [16] to minimize the gap between demand and energy supply. Even though renewable energy has been suggested, they are highly unstable. Fuel cells are being investigated as a viable option. The workloads have been scheduled among geographically distributed data centers by using a scheduling algorithm. By using an appropriate scheduling algorithm, the demand for energy is drastically reduced. Stochastic cost minimization algorithm has been proposed for the optimization and scheduling along with an online control algorithm. Another approach used is the receding horizon control method. The probable performance can effectively increase when the energy demand is scheduled properly.

The allocation of data centers is influenced by the reduction of loads. Inefficiencies in demand response of data centers are shown by cloud service providers that operate on geo-distributed data centers. A proximal Jacobian multiplier algorithm alternating direction approach has been used in Zhou *et al*. [17] to find a solution to the small data center industries by data centers. Coincidence high pricing is the most useful application in data centers. The smart grid process is very useful in the future because the data center demand response has great priority. Cloud service provider (CSP) decides to manage the data center workload to optimize the use of intelligent grids. This paper discusses the various types of demand response strategies. Software-based, hardware-based and power source types are demand response strategies. In addition, time and space load shifts manage power load. Participation in a geo-distributed data center demand response auction is debated. And there are also discussions about the usefulness of smart grids and CSP.

MirhoseiniNejad *et al.* [18] has developed a novel machine learning (ML) approach for quantifying the thermal heterogeneities in data centers. The cost of supplying cold air at the front of servers may be estimated using the thermal models, along with the cooling capacity of servers. The proposed ML algorithm distributes tasks to cooling-efficient locations and has adjusted the cooling unit settings in order to optimize the power consumption. The proposed holistic datacenter infrastructure control (HDIC) approach can considerably reduce the power consumption. In the paper, Al-Moalmi *et al.* [19] has optimized the power consumption in data center by addressing the container and virtual machines (VM) placement problem. Existing methods have solved this issue by using basic heuristics to the problem of container placement and applying a more complex technique to the problem of VM placement. The two search areas are therefore separated by the current techniques. In this work we propose to handle these two phases of placement as one optimization problem an algorithm based on the whale optimization method. The suggested approach has been tested against current techniques by various degrees of diverse settings. The experimental findings have indicated that the suggested technique is superior to the comparative methods in the test setting.

According to Kushwaha *et al.* [20] data centers are becoming more important as businesses become more reliant on data. This leads to an increase in energy usage. This paper gives us to follow better metrics and criteria to increase data centers efficiency. The efficiency of energy is a challenging factor as data centers use a lot of energy. Green grid is a crucial factor for the metrics categorization. The metric should be clear, simple, accurate, precise, and capable enough to act to the need of. Carbon footprint, total cost, uptime, and downtime all the factors should be given importance for the better categorization of metrics. Power of information technology (IT) equipment to the total facility gives data center infrastructure efficiency. Data center power lighting density, server usage effectiveness, and uninterruptible power system efficiency is considered for energy consumption metrics and the power utilization is clearly given in Figure 1. Server centric method helps the server to run efficiently without any interruption caused. Inter server communication latency helps when many servers are in the queue because delay in processing leads to network traffic which affects the performance of the data centers. Each metric plays a very important role in metrics categorization and the comparison is given in Table 1.

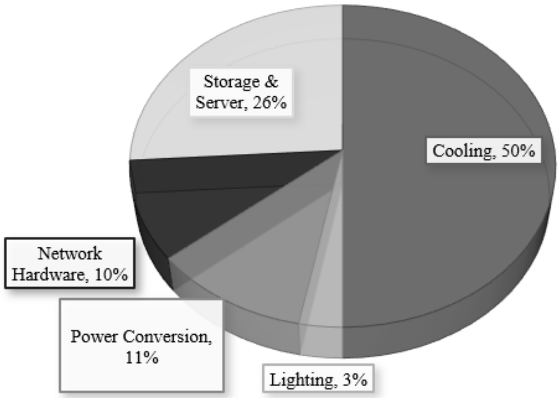

Figure 1. Power utilisation in data center [21]

Table 1. Comparison of research approaches

Researcher	Concept	Comments
Gao [22]	Machine Learning-ANN	PUE is measured, and it is authenticated in Google DC
Lazic *et al.* [23]	Reinforcement learning	Airflow regulation was performed It has a high execution time.
Hu *et al.* [16]	Scheduling, receding horizon control method	Performance is improved
Chou *et al.* [24]	PSO, DPSRA, LSR	The resources were allocated efficiently; however, it has implemented lots of algorithms thereby increasing the complexity.
Zhou *et al.* [17]	Jacobian Multiplier	Power Management is improved.
Lillicrap *et al.* [12]	Deep reinforcement learning (DRL)	High simulation costs and high robustness.
Xia *et al.* [13]	Embedded System with Machine Learning	Enables effective management of resources
Li *et al.* [14]	Recursive Autoencoder	Comparatively lower accuracy
Zheng *et al.* [15]	PowerNets Model	Has potential to save power
MirhoseiniNejad *et al.* [18]	Neural Networks	Quantified the thermal heterogeneities in data centers
Al-Moalmi *et al.* [19]	Whale Optimization	Container and VM Placement

3. BACKGROUND OF THE STUDY

As the complexities of data centers are high along with large data, it is an ideal environment for machine learning. The latest data centers have a large variety of devices, as well as the set points and control schemes that go with it. Traditional engineering models are difficult to use to correctly estimate DC performance d`ue to the relationships between these devices and multiple feedback loops. A slight change in the temperature setting can lead to a large change in load in the equipment, resulting in nonlinear differences in equipment performance. The resulting data center quality would also be influenced by ambient environmental conditions and equipment controls. Since traditional formulas struggle to catch such complex interdependencies, they often generate significant errors when used for predictive modeling [25].

Because there are so many different equipment configurations and fixed-point values, figuring out where the best utility can be challenging. In a live data center, several different combinations of physical equipment and software can be used to reach the target set points (control strategies and set points). Given time limitations, constant variations in the IT load and weather conditions, as well as the need to sustain a consistent data center setting, testing each and every function combination to optimize performance would be impossible [26]. A neural network is chosen as the statistical system for training the algorithms in DC to solve these challenges. Neural networks use artificial neurons to simulate cognitive behavior. Speech recognition, image analysis, and autonomous virtual agents are examples of popular applications for this branch of machine learning. The model consistency increases over time as new training data is obtained, as it does in most learning systems [27]. Deep mind successfully proved that, with the help of machine learning, it is conceivable to increase data center power use efficiency (PUE). They created a prediction model, demonstrating that power consumption may be enhanced by adjusting cooling tower water temperature and water-injection set points [28].

4. METHOD

The aim of this study is to perform a literature review in order to determine the most efficient method of data center cooling energy consumption optimization using machine learning techniques. The research questions (RQ) that direct the work are described around three perspectives i) the degree of efficiency in data center power optimization, ii) the methods employed for improving the energy consumption, and iii) main machine learning algorithms used for optimizing the power usage in the data centers. Table 2 presents the research questions of study and describes the concept along with the related motivation.

Table 2. Research questions

Research Questions	Motivation
RQ1: How efficient is the power optimization of the data centers?	To identify the current status of the power optimization, and to see the quantity of power used and wasted in the data centers
RQ2: What are the different concepts to improve the data center optimization?	To learn about the different methods like virtualization, resource management, clustering, etc.
RQ3: What machine learning algorithms are used to optimize the data center energy usage?	To identify the most suitable algorithm. Each algorithm works differently for various applications. Hence, different algorithms must be compared to identify the algorithm that works well.

The review was performed by collecting research articles from high-standard sources and databases like IEEE, Elsevier, and Springer. Other reputable publications in the field of machine learning-based optimization were also considered. The analysis is limited to papers published from 2015 onwards that use various machine learning algorithms and bio-inspired approaches to optimize data center energy consumption. This paper examines and summarizes these papers in greater detail. The search terms that were used are "*Machine Learning*", "*Data Centers*", "*Energy Optimization*". While there are surveys existing in this field, this paper aims to review the latest articles in this domain, and to identify the gaps in the comparatively newer literature. Only journals with a less percentage of conference papers are eligible, and the papers must be written in English. When the articles are selected, the following steps are performed: i) any repeated content are removed, ii) the inclusion and exclusion criteria are used to filter the results. As given in the previous section, the inclusion criteria of the collected materials are: i) the content must be related to the search string, ii) the published materials must be in English, and iii) out of the collected articles, most of them were journals, while few conference articles were selected. Date of publication from 2015 on.

The exclusion criteria followed are generic blogs and websites, unrelated domains, and articles that do not match the search strings. There will be no unfavorable reviews or limitations in the study because papers from reputable journals will be used. The total number of papers, collected, 40 articles are Journal articles, while 8 are conference articles, and 1 reference corresponds to a university dissertation. Out of these 57 references, IEEE database is most used with 34 references collected from IEEE Xplore, followed by six from Elsevier, five from Springer, three each in Arxiv, ACM, and Inderscience. Three other articles are taken from other sources.

5. MAJOR POWER CONSUMPTION MODEL

The major components of data centers include storage devices, computational tools, temperature control devices, electrical power supply systems, and other diverse equipment, while the worldwide energy consumption for data centers is clearly shown in Figure 2 [29]. The data here utilized allow for a more technologically sophisticated and time-consistent approach than usual. For conventional cloud and most newly developed Hyperscale data centers, the data center loads, server virtualization levels and storage estimates are all classified by power use. The energy consumption patterns often seen in data centers, such as servers, storage devices and network devices are studied. Analysts have recorded the number and location of large data centers, which constitute a substantial part of all computer centers throughout the globe, and big data center operators are gradually revealing their efficiency (PUE). Data management tools are a set of systems for the processing, administration, and routing of data. The data is sent to servers via the storage equipment, while the data management tools are a collection of devices that process, manage and route data. It is also responsible for data replication in other data centers for backup storage. Data processing consumes the greatest proportion of energy [30]. Other devices that consume a lot of energy is cooling systems, which are depicted in Figure 3 as a prediction model of energy consumption. Energy efficiency is highly influenced by the temperature within the data center cooling fans are used to keep the servers and other devices from overheating. When the temperature is high, the computing power is reduced because computations take longer. As a result, it is important to keep the temperature at the optimal level in order to maximize energy efficiency. The energy performance of data centers is influenced by a number of factors. Some of them are the cooling systems, power management and resource management.

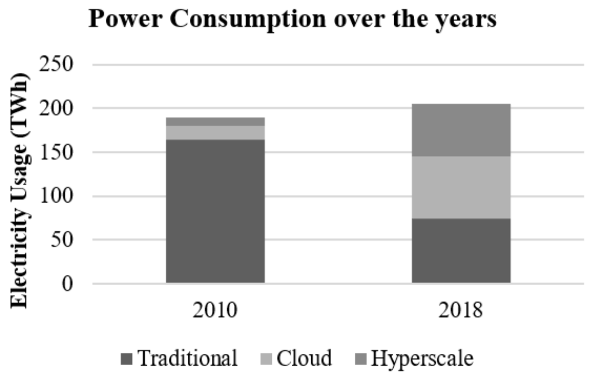

Figure 2. Global electricity consumption for different data centers [29]

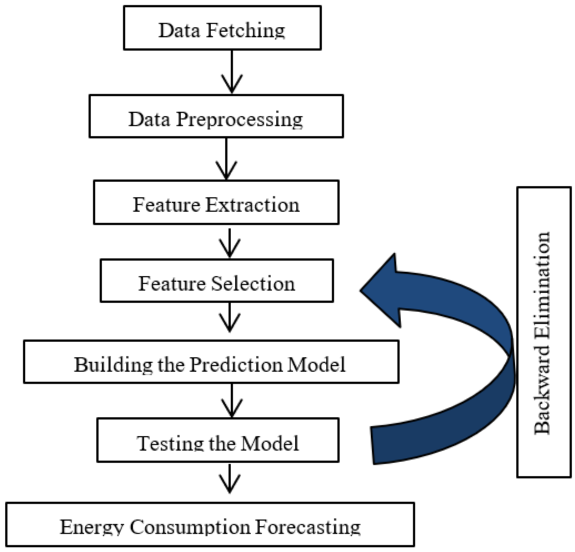

Figure 3. Prediction model for energy consumption [31]

5.1. Cooling infrastructure

The evaporative refrigeration method is used along with excess heat emitted from the systems to sustain the fresh air-cooling system. The two phases of the fresh air-cooling method consist of overt cooling and indirect cooling. The cooling energy may be retained by utilizing the data from a historical sensor. Water- and air-cooling has proven effective as electric chiller-cooling and intelligent sensor placements can be introduced for smart cooling. By lowering the load factors of cooling and power, the power consumption performance benefit may be minimized.

Existing natural cold sources, such as ethylene glycol-based air conditioning systems and clever two-circle energy-efficient air conditioning, can also be utilized. Optimizing power performance is increased by adjusting cooling configurations. In order to improve optimization degree of energy use, black box models have been proposed. It has been demonstrated that the fixed-point environment can be refined by utilizing statistical models to improve data centers' energy performance. The extraction of the data center model for energy quality by data center is the key advantage. Using computer fluid dynamic models, the delivery of cold air to servers can be managed The concept is to use the dynamic simulation modeling approach for efficient usage of power [23].

An implementation based on reinforcement learning has been presented by Lazic *et al*. [23] for temperature control and airflow inside a broad data center. Despite significant advances in reinforcement learning (RL), their usage in physical implementations is still hindered by unexpected circumstances and the risk of costly failures. In taking a model-based approach based on results, it is proved that the RL algorithm can monitor the operational performance faster when compared to established controllers efficiently and securely inside a server floor in a few hours.

Chou *et al.* [24] has proposed a model using particle swam optimization (PSO) for optimizing the cooling in the data center. The proposed dynamic saving resource allocation (DPRA) mechanism is suggested to increase energy performance based on an optimization algorithm for particle swarm. Also, least-square regression approach has been used to mitigate the VM migration. Three well-known allocation mechanisms and one previous solution are simulated and compared to the proposed DPRA mechanism. Cooling devices are one form of machinery that consumes a lot of electricity. The data center's air temperature has a significant impact on energy efficiency. Servers and other instruments are heated continuously and supplied by coolers. When the heat is intense, the computer power is limited since monitoring takes longer. For greater energy production, thus the temperature should be held to the optimal degree. Fulpagare and Bhargav [32] have also researched the optimization of cooling performance to enhance analytical performance. As a result, existing temperature input laws can be effectively achieved by using other electrical devices such as fans and blowers. Physical principles related to the thermal environment, on the other hand, are needed for better and more efficient system operation.

5.2. Power management

Large companies and industries have started to adopt renewable energy for reducing their load demand on the grid. Job scheduling techniques can also be used to determine the amount of solar energy available at a given time and location. Methods like optical technology devices, virtualization, and routing algorithm can optimize the way energy is used and enhance power management. Black box models have been proposed to enhance the optimization level of power usage. Predictive models can help data centers optimize their set points and increase their energy consumption. Extracting a DC model may improve the energy consumption of the data center. Also, cooling directly influences the power consumption, therefor delivering cool air to the equipment can improve efficiency. Care must be taken to regulate the flow of cool air since cooling also consumes energy. Dynamic simulation modeling methods can be further used for power usage effectiveness and create a power management system. Using a power management system may control the hosts and network entities of data centers, by optimizing monitoring, configuring and controlling of power [24].

A deep learning-based novel power prediction model has been proposed by Li *et al.* [14] based on outlining the dynamic power. The energy efficiency is affected by higher power consumption devices. Current problems, such as estimation and static models, neglect the load's dynamic fluctuating existence and ignore the power to load characteristics. The clusters in the noise have been identified in various studies, and the interferences have been reduced. Dual prediction models based on deep learning has been used, including Autoencoder for predicting the power dynamics. As compared to current models, the error has been decreased by more than 79 percent, as shown by the findings

Fu *et al.* [33] have demonstrated the advantages of utilizing cloud-based data centers with apps that need greater capacity and quicker queries, with encryption and search capability. Sánchez *et al.* [34] have studied the higher degree of authorization and usage data management under standardized data stocking, reported another case study for applications that involve identity management (IDMs). Furthermore, Abolfazli *et al.* [35] has studied the cases that reveal that cloud-based services can be extremely effective to increase mobility devices. Also, Cabarcos *et al.* [36] has demonstrated that, considering the distributed existence of the system, it is still possible to handle consumer data in a streamlined manner on the cloud.

While the above papers have optimized the data for cloud systems, specific cloud-based optimization has to be studied by the following authors. Lee *et al.* [37] has reported the initial issue with balancing loads with large data volumes and high users. The framework for the purposes of satellite transmission deals with a larger volume of video content. There was a substantial pause in production power for this application. The initial cloud load balancing research has been performed based on this. Grzonkowski and Corcoran [38] has formulated these initial outcome. However, this approach only used unique charging methods for few applications. Palanisamy *et al.* [39] has used load types that vary with the increase in load balancing strategies to resolve the shortcomings of previous work.

Fan *et al.* [40] has suggested the first of the standardized approach for warped loads. At that time, apache named Hadoop developed the application and load control system. The lack of scalability of the load balancing methods was one of the main disadvantages of the method. The framework needs a higher degree of resource queue configuration for each new load forms. The academic group then began to recognize the need to refine load balancing algorithms. Matsunaga *et al.* [41] carried out noteworthy survey work validating the usage of machine learning-based load balancing algorithms. The research has explored the ability of machine learning approaches to decrease the difficulty of time of the load balancing strategies.

On the other side, another solution included the recognition and machine learning (ML) approaches are being implemented in order to validate the availability of computer resources. This idea was elaborated by Piao and Yan [42] and various recognition and modeling of the pattern of resource usage have been used for each virtual machine. The modelling needs higher complexity handling ML, as shown by Wood *et al.* [43], the key to a successful development of the right load balance algorithm is ideal load simulation and the use of virtual resources. This research also advances a deep learning technique for load balancing [44]–[47]. Unilateral random sampling has been quantified for the method to which a coordinated diagram is referred. It is seen that open properties for each execution hub represent allocated occupations. During the occupation, the degree declines, and after job allocation, the out-degree rises. Clustering dynamics is a machine redesign estimate [48]–[51].

5.3. Resource management

Virtualization techniques for servers and an optimized storage supply can maximize resource utilization. The energy output of system power can be measured using consumption efficiency and output per watt. There is a power optimization algorithm that monitors load allocation and lowers data center operating costs. The two approaches used to minimize energy consumption on servers are dynamic frequency scaling and dynamic power management. It decreases the server's power consumption if the servers go to sleep mode. The control of power mapping is quite critical. The combination cooling of gas district and data center control model can be extended and used to minimize pollution releases by applying a refrigerated water source gas model. Hadoop MapReduce may be utilized to measure the energy efficiency by aggregation. It is not quite effective to adapt the power supply to store the use of small loads. These challenges are also being taken into account, and collaborative workload preparation and energy efficiency are through changing energy demand and data center distribution. The monitoring of fuel cell production is suggested to minimize the difference between the availability and energy demand of an online algorithm. The fuel cell monitoring can overcome the existing issues like charging the batteries optimally and considering the costs.

Large data centers encounter more challenges, such as hardware and device glitches, contributing to inconsistency in system efficiency and ultimately reduction of quality of service. The most common solution is to combine VMs, a strategy that seeks to bundle as many VMs as possible into one single physical host, to increase the energy and resources performance of data centers [52]. In addition, the live VM migration enables a complex aggregation of VMs to maximize energy efficiency and better VM location by swapping idle hosts on low power modes. The low-power modes of recent servers, which are more energy effective and transfer overhead, allowing more savings compared to conventional switch-off technologies. If dynamic consolidation is not successfully implemented, it can degrade QoS and improve the power usage, and the overall overhead of migration and power-mode transformations [53].

Aside from the challenges, posed by internal and external sources like outdated or malfunctioning infrastructure, thermal management, orphan processes or operating system problems, technology variability is one of the main challenges in DC [54]. Most of these abnormalities cause deterioration of output during host operation, and hence degradation of QoS [55]. The identification of output fluctuations is typically made by continuous device reports in real-time. The number of measurements to be acquired and evaluated is important, as the dimensions of data centers expand. The manual processing of this amount of data is, therefore not feasible, and techniques to identify and separate servers with a severe level of efficiency variability need to be established automatically [56].

A novel centralized strategy for larger scale data centers has been proposed in Haghshenas *et al.* [57]. The approach has utilised a distributed and high aware VM approach with lesser overhead. The approach has selected the most suitable frequency and type of power for the hosts while running the VM by using a machine learning-based distributed strategy. The virtual machine is migrated using central heuristics. The proposed model was developed using the CloudSIM simulation method and takes into account the delay overhead. In comparison to current methods, the proposed solution has decreased data center energy consumption by 15%. It also has the same QoS and has cut the number of virtual machine migrations and host energy mode transformations by up to 86% and 90%, respectively.

Baccour *et al.* [58] have reviewed the designs of DC with respect to power usage. Quality of service components must be included in the centers, according to the concept. Sources of energy have been suggested to compensate for the electricity demand along with power-aware routing algorithms. There are some issues identified, which are idle networks, inadequate cooling infrastructure maintenance and the usage of brown electricity. Large businesses are investing in growing ventures on renewable energies, such as wind and solar. A work scheduler may be used to calculate the quantity of solar energy that would be required for the future. They should incorporate free refrigeration mechanisms in data centers with air or water instead of utilizing electric chillers. Equipment like optical infrastructure, commodity networks, and cellular infrastructure may be utilized by data centers to reduce the usage of energy. Dynamic power control can be accomplished through four algorithms: Adaptive connection rate, power algorithms, virtualization, and dynamic voltage/frequency scaling. The three options to solve the issues, which are natural power sources, powerful equipment and interconnections, clean cooling and heat disposal, and power-conscious algorithms were suggested.

By utilizing the clustering and virtualization approaches, server groups can be built with identical subnet masks. This approach decreases energy usage significantly. The mechanism for interlocking gas generators and grid power used to design data centers is not very effective. In the architecture of data centers, the mechanism of electric interlocking is therefore favored. To decrease the power of the chiller the generator load is increased, by raising its performance. To maximize performance, between 90% and 100%, more heat must be extracted from the data centers, which necessitates the use of generator power. One of the easiest approaches to minimize electricity use is by eco-clouds. This would significantly eliminate fossil footprints. Dynamic or successful implementation, such as migration, is strongly recommended since they boost the efficiency of cloud apps. The new demand response in data centers is inadequate. Proximal Jacobian multiplier approach alternate path helps overcome the small-scale data center crisis. The electricity grid is also proposed to develop into an intelligent infrastructure. In comparison, parallels, and demand and answer variations in data centers improve data centers' performance.

6. CHALLENGES, GAPS, AND RECOMMENDATIONS

Data center's computer servers are usually in the on state continuously and waiting for data, so the processing in the system absorbs a lot of energy. There is an appropriate way to store and process enormous data efficiently [21]. Then the network gets optimized, and only switches on, when necessary, then it leads to several problems. The carbon dioxide emissions from the computer server are comparable to those from sports cars. The use of brown energy releases carbon into the atmosphere and aids in climate change. By adopting different methodologies and techniques, the power efficiency, and hence the carbon footprint of the data centers can also be minimized. The amount of network traffic varies depending on whether or not DC networks are used. For this reason, over-provided resources, such as redundant servers, network and stock equipment, should be installed and supplied with 2 power sources to ensure that the system works when high loads and system breaches occur [59].

The energy usage of DCs decreases when there is a power failure in the UPS. Energy management in data centers is a very serious problem. The conventional power systems are less efficient; however, the dynamic circuit networks reduce energy waste by making use of host-cantered data center networks. In existing systems, it is not very efficient to adjust energy supply for storage use with a limited load. The fuel cell of the polymer electrolyte membrane lowers the working temperature, increasing costs. Models of energy management were skewed in relation to fuel cell electricity supplies to data centers. The footprints of fuel cells are smaller, but there are not sufficient to handle the heavy loads. The system uses power grids to maintain data center operational stability. But the energy grid problems are now changing to intelligent grids. The conventional data centers have no potential to respond to demand. In terms of data demand response programs in data centers, prioritize peak pricing, which isn't very efficient. While considering these problems, new models, and approaches in order to improve energy efficiency consumed by data centers are found in the existing system.

Power management in the existing system is carried out through temporary and spatial load shifts. The inlet temperature should be high on the rack to reduce the power consumption in the data centers. Measurements of airflow, water flow rates and refreshing turbines are rarely accessible, as are temperatures of the engaged fluids supplied and returned. They can improve energy efficiency by decreasing leak power in data centers. Efficiency is very critical in the design of data centers, when the efficiency of data centers is taken into account the combined cooling, heating, and power factors. Economically, the trigeneration system is better suited than cogeneration. Gas generator and power grid mechanisms that are employed in the design of data centers are not very efficient. The categorization of metrics in data centers is extremely important because the data centers require a high level of business demand. In improving the efficiency of data centers, each metrics plays an important role. By taking into account these challenges, the proposed systems for improving energy efficiency at data centers explain certain design techniques, methodologies, and various mechanisms. While there are lots of different algorithms in the document, there is very research on bio-inspired approaches. It is well known that bio-inspired approaches work well for optimizing parameters, however, there are very few research conducted for optimizing the variables in a data center [60]. Also, neural networks are known for higher complexity problems. Gao [22] has used neural networks effectively for reducing the PUE in data centers of Google Cloud. While both of these approaches work well independently, the parameters would get better optimized when both are combined together.

7. CONCLUSION

This paper has provided a summary of the challenges faced by data centers to optimize the energy efficiency. Different data center optimization approaches were discussed, and it is seen that there are some gaps. The existing data center cooling approach are not very efficient and still have a large scope for improvement in the data center power consumption efficiency. Existing research has utilized a variety of techniques, but deep learning appears to be the most efficient. Several solutions that could be applied to solve the problem faced by the data centers has been reviewed. These systems are proposed to reduce electricity, greenhouse gases, carbon footprints and the cost problem. In order to further develop the data centers, in-depth research is required in this area. The energy performance of the data centers is directly influenced by the temperature and the power consumption by the equipment.

This paper reviewed the different parameters of performance for effective optimization of power. The cooling may be effectively optimized by varying them at different temperatures, and by optimizing its flow. This paper explored the problem by examining previous methods to estimate energy consumption from the computer architecture area. A state-of-the-art on machine learning approaches and bio-inspired techniques were presented by reviewing the most recent literature. The novelty of this paper arises from the review of recent papers and identifying the limitations. From these limitations, recommendations are given to make improvements in the future. Efficient utilization of physical space and electricity capacity is the primary problems of implementing data center optimization. Although the techniques of power optimization may be addressed using above-mentioned optimization methodologies, another issue is the physical space of big devices. It may also be hard to constantly optimize power owing to dynamic variations in load. The owners and vendors of data centers should, however, always strive for productivity since this entails lower maintenance costs, improved availability, and increased utilization of available resources.

8. FUTURE WORK

Various machine learning algorithms have been performed to optimize power. However, the existing methodologies have high computational time. For quicker computing, basic machine learning methods can be used for single location of data center or small data center. However, for large data centers to handle lots of data or for multi geographic located data centers, high computational algorithms are necessary. Hence, neural networks would be more suitable for higher computations. Also, since bio-inspired approaches work well for optimizing parameters, it can be used in the future research conducted for optimizing the variables in a data center. In this work, a combination of a bio-inspired algorithm and neural network approach can be combined and considered as a future scope.

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