Review on Carbon Aware Cloud Computing for AI

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Abstract

Climate change crisis is an urgent global threat, and the rapidly increasing carbon footprint of AI workloads in cloud computing infrastructures necessitates immediate action. This survey paper investigates the field of carbon-aware cloud computing for AI, emphasizing the integration of carbon efficiency into AI cloud services. This paper mainly focuses on key challenges highlighted in the literature, including but not limited to the lack of transparency and disaggregated control over carbon emissions between cloud providers and users, the significant effort required for developers to implement carbon-aware optimizations, and the growing complexity of resource management due to renewable energy variability and hardware heterogeneity. By reviewing techniques like carbon budgeting, enhanced service-level emissions visibility, and configurable centralized resource management optimizations, this paper provides a detailed overview of current approaches and their effectiveness. This survey highlights the necessity for integrated carbon efficiency practices in cloud computing and encourages collaborative action among all stakeholders to promote sustainable AI development.

Keywords

Carbon-Aware Computing, Sustainable AI, Carbon and Efficiency-Aware Compute Management, Cloud Computing for Carbon Reduction, Sustainability in Computing

1 Introduction

The recent climate crisis, driven by increasing greenhouse gas emissions, has underscored the urgent need for industries worldwide to adopt more sustainable practices. Among the most significant contributors to global emissions are the energy-intensive operations of data centers, which support cloud computing services and artificial intelligence workloads such as LLMs. Data centers and servers that work 24 x 7 to meet the demands of modern applications consume vast amounts of energy, and this energy consumption is responsible for approximately 2.5 - 3.7 percent of global greenhouse gas emissions. This environmental impact now exceeded that of the aviation industry. As demand for AI-driven services continues to grow, the carbon footprint of these AI workloads has become an area of increasing concern.

AI, particularly in cloud computing environments, has a substantial environmental footprint due to the enormous computational resources required for both training and inference. These tasks often require massive amounts of energy and computing power, leading to significant carbon emissions. Embodied carbon emissions—those generated during the production of the hardware used in data centers, such as CPUs, GPUs, and servers—also contribute to the overall carbon footprint. While reducing embodied carbon is challenging due to the inherent resource-intensive nature of hardware production, operational emissions, which occur during AI training and inference, offer a more tangible opportunity for improvement. By optimizing how AI models are trained and how resources are allocated during inference, carbon emissions can be significantly reduced.

Recent studies have highlighted the potential for AI workloads to contribute significantly to carbon emissions. For instance, training large-scale AI models can result in emissions equivalent to five times the lifetime emissions of a typical car. However, research also shows that substantial reductions in carbon emissions are possible through algorithmic optimizations and better resource management. A study by Google, for example, demonstrated that by refining AI training processes, emissions could be reduced to as low as 0.00004 lifetime car emissions—an almost negligible amount compared to previous methods. This stark contrast emphasizes the effectiveness of optimization techniques in minimizing the environmental impact of AI, particularly in cloud computing settings.the concept of carbon-aware cloud computing has emerged as a promising solution. Carbon-aware cloud computing aims to reduce the carbon footprint of AI workloads by optimizing their alignment with renewable energy availability. Many cloud providers are striving to integrate renewable energy sources such as wind, solar, and hydroelectric power into their data center operations. However, renewable energy is inherently intermittent, with availability fluctuating based on time of day and weather conditions. As such, cloud providers face the challenge of balancing performance needs with the goal of minimizing carbon emissions by scheduling workloads to run during periods when renewable energy is abundant.the heterogeneity of cloud infrastructure further complicates the adoption of carbon-efficient strategies. Data centers utilize a wide range of hardware, each with different energy consumption profiles, making it difficult to implement one-size-fits-all solutions. This diversity requires more nuanced resource management techniques to ensure that workloads are efficiently distributed across the available hardware while minimizing energy consumption and emissions.

Another critical challenge is the lack of transparency regarding the carbon emissions of cloud services. Users typically have little visibility into the environmental impact of the services they utilize, making it difficult for them to make informed decisions about their cloud usage. Without transparency, users cannot optimize their workloads or choose the most carbon-efficient cloud services. This lack of control, combined with the complexity of energy management in cloud environments, highlights the need for greater integration of carbon-aware optimization strategies into AI cloud services.

This paper examines the emerging field of carbon-aware cloud computing for AI, exploring the key challenges, optimization techniques, and opportunities for reducing the carbon footprint of AI workloads in the cloud. By highlighting the importance of transparency, renewable energy integration, and efficient resource management, this paper calls for a collaborative effort to make cloud computing more sustainable and align AI development with global environmental goals. The transition to carbon-efficient AI cloud computing represents a vital step in mitigating the environmental impact of modern technology and advancing toward a more sustainable future.

2 Background Of Cloud Computing for AI

2.1 Cloud Computing:

A technological paradigm known as "cloud computing" makes it possible to provide computer services-like storage, processing power, and apps-over the Internet. Instead of using local computers or on-premises infrastructure, it allows users to access and manage data and applications on remote servers. Due to its scalability, flexibility, and affordability, this approach is a desirable choice for both people and businesses. Generally, cloud computing services fall into one of three primary categories.

2.2 Software as a Service (SaaS):

Software as a Service (SaaS) is a subscription-based online software delivery model. Users do not need to install and maintain these applications on local devices because they can access them using web browsers. Salesforce, Microsoft 365, and Google Workspace are some examples. Enterprise resource planning (ERP), email, and customer relationship management (CRM) are just a few of the corporate applications for which SaaS is widely utilized.

2.3 Infrastructure as a Service (IaaS):

Infrastructure as a Service (IaaS) provides essential building pieces including virtual computers, storage, and networks by delivering virtualized computing resources via the internet. Prominent suppliers comprise Google Cloud Platform (GCP) Compute Engine, Microsoft Azure Virtual Machines, and Amazon Web Services (AWS) EC2. Businesses in need of scalable computing resources for a range of applications, such as web hosting, data processing, and backup solutions, might consider Infrastructure as a Service (IaaS)

2.4 Platform as a Service (PaaS)

Customers can create, execute, and manage applications on a platform provided by Platform as a Service (PaaS) without having to worry about the supporting infrastructure. It offers a foundation upon which programmers can construct unique applications. Heroku, Microsoft Azure App Services, and Google App Engine are a few examples. For developers who would rather concentrate on writing code and launching apps rather than handling server, storage, and networking administration, PaaS is helpful.

2.5 Cloud Computing for AI Workloads:

Cloud computing has become a cornerstone for artificial intelligence (AI) workloads, offering scalable, flexible, and cost-effective solutions for managing the computational demands of AI development and deployment. By leveraging cloud platforms, organizations can access high-performance computing resources, such as GPUs and TPUs, which are essential for training complex machine learning models. Cloud providers also offer AI-specific tools and services, including pre-built machine learning models, data storage solutions, and integrated development environments, enabling faster innovation and reducing the need for upfront infrastructure investment. Furthermore, the elasticity of cloud systems allows organizations to dynamically scale resources based on workload requirements, ensuring efficiency and minimizing costs. As AI applications increasingly require massive datasets and real-time processing, the cloud's ability to handle distributed storage and computation has made it an indispensable enabler of AI-driven advancements across industries

2.6 Edge Computing in Cloud AI Integration:

Edge computing complements cloud computing by bringing processing capabilities closer to the data source. This paradigm is especially critical for AI applications requiring low latency, real-time processing, and localized decision-making, such as autonomous vehicles, IoT devices, and smart cities. Cloud providers are increasingly integrating edge computing with their services, enabling seamless collaboration between centralized cloud resources and edge devices. This hybrid approach enhances the efficiency and scalability of AI systems while addressing challenges related to bandwidth, latency, and data sovereignty.

2.7 Challenges with carbon aware computing:

The agile reduction of cloud carbon emissions faces challenges in visibility, development, and resource management. Visibility into carbon emissions (C1) is limited by inadequate user-level energy measurements, lack of fine-grained monitoring for multi-tenant systems, and safety concerns, while embodied emissions (C2) are inconsistently reported and fail to incentivize extending hardware lifespans. Trust issues (C3) stem from inconsistent, unverifiable emissions reporting by cloud providers. Carbon-aware software development is hindered by application complexity (C4), as large-scale applications rely on microservices and legacy systems, and a lack of developer tools (C5) to optimize carbon efficiency. Resource management faces challenges from renewable energy variability (C6), requiring adaptive scheduling across regions and timescales, and hardware heterogeneity (C7), where diverse architectures (e.g., CPUs, GPUs, TPUs) offer varying carbon trade-offs. Addressing these challenges necessitates transparent carbon accounting, standardized reporting, developer tools, and optimized resource management to enable an agile, carbon-efficient cloud ecosystem.

3 Carbon Reduction:

Finally, to simplify operator efforts for cloud-managed services, we propose that providers centralize carbon-aware resource management mechanisms and expose configurable knobs to operators (R3). Optimizing cloud-managed services using black-box approaches quickly runs into limitations since many carbon optimizations involve multidimensional trade-offs beyond provider purview. For example, older hardware may run services slower and less reliably but offer higher carbon efficiency [83]; carbon-aware scheduling may delay workloads so they run during low carbon intensity time periods [69, 93]. To communicate these trade-offs, operators should be able tweak static or dynamic knobs that cloud providers can rely upon to make better carbon-aware optimizations. Centralizing optimizations particularly benefits agility by eliminating redundant optimization efforts across different services and across operators.

3.1 Static Optimizations:

Operators should be able to communicate known static trade-offs to providers upon service creation or deployment. To implement static hints, providers could simply require operators to pass an appropriate flag when deploying cloud-managed microservices. For example, operators could indicate that a service is delay tolerant, letting providers schedule it when renewable energy is available [93]. Alternatively, providers could create new cloud platform offerings like "green VMs" which could be carbon-aware alternatives to spot VMs or harvest VMs that are spun up only when the carbon intensity of energy is low [7, 75]. Although carbon-aware scheduling already exists for internal workloads in some clouds today [69], we note that building such static optimizations into cloud-managed services enables users to benefit, as well.

3.2 Dynamic Eco Modes

Inspired by eco mode dials in modern cars [47], we propose that operators be able to dynamically specify simple hints to help the cloud platform improve carbon efficiency. For example, operators could signal that a service has latency slack, letting providers run it at lower clock frequencies (reducing operational emissions) or on older CPUs (reducing embodied emissions). Developers can further utilize eco modes to implement carbon-efficient application functionality, such as by using different eco modes to serve machine learning models that offer different accuracy, performance, and efficiency trade-offs for the same application task. To enable eco mode settings in the cloud, providers must implement a communication interface between the application service and the cloud platform. As a first step, most existing cloud monitoring systems allow specification of custom metrics, and this interface could be extended to communicate eco modes. In the future, cloud providers could expose a dedicated eco mode interface to operators. Each eco mode could capture different carbon trade-offs, and multiple modes could be combined for greater carbon reduction. For example, a delay-tolerant eco mode might use renewable-aware scheduling or lower compute clock frequencies [65]. A reliabilitytolerant eco mode might schedule applications on older hardware generations to reduce carbon emissions [83, 86]. A balanced eco mode could schedule latency-sensitive applications interchangeably on heterogeneous compute workers to strike a middle ground between their spin-up latency, cost, and energy efficiency

3.3

To help operators make informed decisions about available static optimizations and eco mode trade-offs, providers could monitor historical user workloads, use simple simulators/predictors to determine potential carbon savings, and display savings on operator dashboards. For example, if shown that adding new FPGA implementations to existing CPU services could dramatically reduce carbon emissions while only slightly increasing costs [66], operators might be better positioned to make such recommendations within their enterprises based on their carbon and financial budgets. To motivate operators to enable carbon-reduction optimizations, providers could also introduce economic incentives by leveraging lowered operational costs due to reduced energy and power consumption. Prior work on market-mechanism-based power capping is a good starting point for future inquiry in this direction

4 Discussion

The discussion section highlights key aspects, challenges, and future directions in the context of carbon-aware cloud computing for AI workloads. As AI workloads continue to grow in scale and complexity, the demand for cloud computing resources has led to a significant rise in energy consumption, thereby contributing to the increasing carbon footprint of cloud data centers. This growing concern underscores the importance of integrating carbon-awareness into cloud computing practices.

A key implication of carbon-aware cloud computing is the need for greater transparency in emissions reporting. Currently, cloud providers are not always clear about their emissions data, and the metrics they provide are often inconsistent or inadequate. This lack of transparency makes it difficult for users to make informed decisions regarding the carbon footprint of their cloud services. With AI applications becoming more carbon-intensive, it is essential for cloud providers to offer better visibility into the energy consumption of their services. This would allow users to assess the environmental impact of their cloud usage and make decisions accordingly, potentially leading to more sustainable choices. Cloud providers that implement transparent and standardized carbon reporting can also gain a competitive advantage, as businesses increasingly prioritize sustainability in their operations.

Furthermore, carbon-aware software development is a critical factor in minimizing emissions. The development of large-scale cloud applications is often complex, involving millions of lines of code and a combination of microservices. This complexity makes it difficult to directly implement carbon-efficient optimizations. Developers are not typically provided with access to fine-grained energy usage data, which makes it challenging to optimize applications for energy efficiency. Even though some cloud providers offer tools and resources for tracking energy usage, these tools are still in early stages and cannot always be easily integrated into large-scale applications. As a result, there is a need for more advanced developer tools that can help optimize code for carbon efficiency. With such tools, developers could be empowered to make more informed decisions about how their applications impact the environment.

Another significant challenge in carbon-aware cloud computing is the variability of renewable energy sources. Renewable energy sources such as wind and solar power are intermittent, and the supply of clean energy fluctuates depending on environmental conditions. This variability can create difficulties for cloud providers trying to maintain stable and sustainable energy usage. Cloud data centers require constant energy supply to handle workloads, and if the availability of renewable energy is low, providers may need to rely on fossil fuels to meet demand, leading to increased emissions. To address this challenge, cloud providers need to develop better energy scheduling systems that match workloads with renewable energy availability. This would involve advanced resource management systems that can dynamically adjust workloads based on real-time energy supply, reducing reliance on fossil fuel-based energy when renewable sources are scarce.

Additionally, the heterogeneity of cloud hardware further complicates carbon-aware resource management. Modern cloud infrastructures use a variety of hardware components, from general-purpose CPUs to specialized accelerators like GPUs and TPUs. Each hardware type has its own performance and energy efficiency characteristics, making it challenging to optimize the energy usage of workloads. Older hardware, while potentially more energy-efficient in terms of embodied emissions, may not perform as well as newer hardware, leading to trade-offs between performance and carbon footprint. Cloud operators must manage these diverse hardware resources carefully to minimize emissions while meeting performance and cost objectives. The challenge lies in creating optimization algorithms that take into account the specific energy efficiency characteristics of different hardware types and balance these with application requirements.

The success of carbon-aware cloud computing relies not only on technological advancements but also on collaboration among various stakeholders. Cloud providers, developers, and users must work together to integrate carbon-efficient practices into cloud usage. Providers must offer transparent emissions data and develop tools that help users make carbon-efficient choices. Developers must be supported with the right tools and methodologies to design energy-efficient applications. Additionally, policymakers must play a role by establishing regulations and standards for carbon emissions reporting, which would ensure consistency and accountability across the cloud industry.

As AI workloads continue to scale, there are also opportunities for innovation in hardware design. The development of more energy-efficient chips, such as those optimized for AI workloads, could reduce the overall energy consumption of cloud data centers. Additionally, advancements in edge computing, where data is processed closer to the source, could reduce the need for long-distance data transmission and the associated energy usage. By processing data locally, edge computing could help reduce the overall carbon footprint of cloud computing systems.

In conclusion, while carbon-aware cloud computing faces a range of challenges, it offers significant potential for reducing the environmental impact of AI workloads. The path forward will require collaboration among cloud providers, developers, and policymakers, as well as continued research into new technologies and methodologies for optimizing energy use. With the right tools, transparent reporting, and a focus on sustainability, the cloud industry can play a crucial role in reducing global carbon emissions and fostering a more sustainable digital future.

5 Conclusion

In conclusion, carbon-aware cloud computing represents a critical step toward mitigating the environmental impact of the rapidly growing AI and cloud industries. This paper has identified the primary challenges, including limited visibility into emissions, the complexity of carbon-aware software development, and the difficulties of managing heterogeneous resources in alignment with renewable energy variability. These challenges underscore the need for transparent emissions reporting, developer-focused tooling, and advanced resource management strategies.

The proposed framework addresses these gaps by offering a comprehensive approach that integrates real-time emissions tracking, standardized reporting methodologies, and intelligent workload scheduling. By leveraging tools and methodologies that prioritize sustainability without compromising performance, the framework aligns with both industry objectives and global carbon reduction goals.

Furthermore, stakeholder collaboration is essential for achieving meaningful progress. Cloud providers, developers, and policymakers must work together to establish robust standards, incentivize sustainable practices, and foster innovation in carbon-efficient technologies. As the field evolves, future research should explore advancements in energy-efficient hardware, AI-driven optimization, and decentralized computing models like edge computing to further minimize carbon footprints. Ultimately, embracing carbon-aware practices is not just an environmental imperative but also a strategic opportunity for the cloud industry to lead the way in sustainability. By integrating these principles into their operations, stakeholders can ensure that the benefits of AI and cloud computing are realized without compromising the health of our planet.

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