Analyzing the Total Cost of Ownership of Carbon in Data Centers

Mitchell Elliott
miclelli@ucsc.edu
UC Santa Cruz
Santa Cruz, California, USA

Andrew Quinn
aquinn1@ucsc.edu
UC Santa Cruz
Santa Cruz, California, USA

Heiner Litz
hlitz@ucsc.edu
UC Santa Cruz
Santa Cruz, California, USA

Abstract

In recent years, the environmental impact of data centers has become a significant concern due to their high energy consumption and carbon emissions. A substantial portion of a data center's carbon footprint is attributed to the embodied carbon cost of its infrastructure, particularly storage media. This study analyzes the total cost of ownership (TCO) of carbon in storage-heavy data center workloads, with a particular focus on the belief that glass-based storage solutions may offer a lower total carbon burden than any other type of storage. Specifically, this study compares solid-state drives (SSDs), hard disk drives (HDDs), tape, and emerging glass-based storage solutions, which vary significantly in their energy efficiency, longevity, and environmental impact.

This paper presents *CarbonStream*, a TCO simulator for a three-tier video streaming platform. It accepts a variety of inputs, such as the embodied and operational carbon costs for a set of hardware, as well as the SLO latency and throughput values that the system must meet. It then calculates the carbon usage of the system over a specified duration, which can be used to determine the most efficient set of hardware to use, given the set of constraints.

Using *CarbonStream* to simulate a range of video streaming workloads, we provide a comprehensive comparison of the energy efficiency and carbon impact of each storage technology. The analysis considers both the operational energy costs and the embodied carbon inherent in the production, use, and disposal of these storage media. Our findings reveal significant variations in the carbon footprint of different storage solutions, underscoring the potential for substantial environmental savings through informed selection of storage technologies.

1 Introduction

Data centers are the backbone of the digital economy, supporting everything from cloud services to online transactions, data analytics, and artificial intelligence. As demand for digital services continues to grow exponentially, so does the energy consumption of data centers, making them significant contributors to global carbon emissions [5]. Although much attention has been focused on reducing the operational energy consumption of data centers, such as optimizing cooling systems, improving server efficiency, and transitioning to renewable energy sources, another critical aspect of their environmental impact often goes underappreciated: the embodied carbon cost of their infrastructure.

Embodied carbon refers to the total greenhouse gas emissions generated during the lifecycle of a product, from the extraction of raw material through manufacturing, transportation, installation, maintenance, and disposal [9]. In the context of data centers, this includes the carbon footprint of servers, storage devices, networking equipment, and other critical infrastructure components. Among these, storage media represent a substantial portion of the embodied carbon footprint, especially in storage-heavy workloads where vast amounts of data are processed and stored.

This paper addresses the need to evaluate the total cost of ownership (TCO) of carbon in data center storage technologies, with a particular focus on the belief that glass-based storage solutions may offer a lower total carbon burden than any other type of storage. Specifically, this study compares solid-state drives (SSDs), hard disk drives (HDDs), tape, and emerging glass-based storage solutions, which vary significantly in their energy efficiency, longevity, and environmental impact. Although SSDs and HDDs are well established in the industry, tape storage remains a viable option for long-term archiving because of its low operational energy consumption. Glass-based storage, although still in its infancy, promises to revolutionize data storage with its potential for high durability and low environmental footprint [2].

We believe that glass-based storage can potentially replace existing media in data centers by offering a lower total carbon burden. This paper aims to validate this belief through a detailed analysis of the embodied carbon costs associated with different storage technologies, providing valuable insights for the future of data center storage infrastructure.

Given the urgent need for sustainable data center practices, this study leverages *CarbonStream*, a custom-developed simulation model, to estimate the embodied carbon and energy consumption associated with different storage technologies under typical workload conditions. By analyzing the trade-offs between operational energy costs and embodied carbon, this research aims to provide data center operators, policymakers, and researchers with actionable insights to make more informed decisions regarding storage infrastructure.

The remainder of this paper is organized as follows. The *Background* section reviews existing literature on carbon footprints of data centers, with a focus on storage media. The *System Design* section details the model of *CarbonStream*, including the assumptions, metrics, and parameters for each storage technology. The *Evaluation* section presents the simulation results, comparing the total carbon impact of each storage technology. The paper concludes with a discussion of the findings, their implications for sustainable data center operations, and suggestions for future research in the *Conclusion* and *Future Work* sections.

2 Background

The environmental impact of data centers has been increasingly subjected to scrutiny as demand for digital services continues to surge. These facilities, which power everything from social media platforms to cloud computing services, are responsible for a substantial share of global electricity consumption and carbon emissions. The focus of environmental efforts in data centers has traditionally been on reducing operational energy consumption through strategies such as improving cooling efficiency, optimizing server workloads, and adopting renewable energy sources. However, this approach overlooks a critical component of the carbon footprint: the embodied carbon associated with the manufacturing, deployment, and disposal of data center infrastructure.

2.1 Embodied Carbon in Data Centers

As mentioned earlier, embodied carbon refers to the total greenhouse gas emissions produced during a product's lifecycle. In the context of data centers, embodied carbon is a significant, yet often underappreciated, contributor to the overall carbon footprint. The construction of data centers, the production of servers, storage devices, networking equipment, and other components all contribute to embodied carbon. For storage-heavy workloads, where vast amounts of data must be reliably stored and accessed, the embodied carbon of storage media becomes a particularly critical factor.

2.2 Storage Technologies and Their Carbon Impact

Over the years, various storage technologies have been developed, each with unique characteristics in terms of performance, energy efficiency, and environmental impact. The most common storage media in data centers today include solid-state drives (SSDs), hard disk drives (HDDs), and tape. More recently, glass-based storage has emerged as a potential alternative, promising greater durability and a lower environmental footprint.

2.2.1 Solid-State Drives (SSDs)

SSDs are known for their high performance, with fast read/write speeds and low latency. They are typically used in environments where speed and reliability are critical, such as in primary data storage and high-performance computing applications. However, the production of SSDs involves significant embodied carbon, particularly due to the complex manufacturing processes required for flash memory chips. Despite their energy efficiency during operation, the high embodied carbon cost can make SSDs less favorable from an environmental perspective over their lifecycle [20].

2.2.2 Hard Disk Drives (HDDs)

HDDs have been the workhorse of data center storage for decades. Although they are generally less energy efficient than SSDs during operation, their embodied carbon cost is lower due to simpler manufacturing processes [7]. HDDs are typically used in applications where high capacity is required but speed is less critical, such as archival storage.

2.2.3 Tape Storage

Tape storage is a longstanding technology primarily used for archival purposes. Tapes have a very low operational energy footprint, making them an attractive option for long-term data storage. The embodied carbon of tape is also relatively low, as the materials and manufacturing processes are less resource-intensive compared to SSDs and HDDs [6].

2.2.4 Glass-Based Storage

Glass-based storage is an emerging technology that has the potential to revolutionize the industry. By using glass as the storage medium, this technology offers exceptional durability and potentially lower embodied carbon due to the minimal material requirements and longevity of the medium. While still in the experimental stage, glass-based storage has the potential to provide a sustainable alternative to traditional storage media [15].

2.3 Previous Research on Data Center Carbon Footprints

Previous studies on data center sustainability have predominantly focused on reducing operational energy consumption. Techniques such as dynamic voltage and frequency scaling (DVFS) [8], utilizing renewable energy sources (Ecovisor) [19], and workload balancing (Carbon-Aware Computing) [16] have been widely explored. However, the embodied carbon of data center infrastructure has received comparatively less attention. Some research has begun to address this gap, such as ACT [11], Chasing Carbon [12], and Carbon Explorer [1], highlighting the importance of considering both operational and embodied carbon to achieve a comprehensive understanding of a data center's environmental impact.

Recent advancements in lifecycle analysis (LCA) have enabled more accurate assessments of embodied carbon across different components of data centers, including storage devices. These studies have underscored the need for more detailed comparisons of storage technologies, particularly as new solutions like glass-based storage emerge.

2.4 Rationale for This Study

Given the evolving landscape of storage technologies and the increasing emphasis on sustainability in data centers, this study seeks to address a critical gap in current research by providing a comparative analysis of the total cost of ownership (TCO) of carbon across SSDs, HDDs, tape, and glass-based storage. By focusing on storage-heavy workloads, this research aims to determine whether glass-based storage truly offers a lower total carbon burden than existing media, thereby providing a foundation for more sustainable data center operations.

3 System Design

CarbonStream is a simulation model used to analyze the total cost of ownership (TCO) of carbon across different storage technologies in data centers. It is designed to simulate various storage-heavy workloads and calculate the associated carbon costs based on the operational characteristics and lifecycle of each storage medium. This section outlines the key components of *CarbonStream*, including the hardware configurations, metrics, assumptions, and parameters used in the analysis. Additionally, it provides a detailed explanation of how the carbon cost calculations, average latency, peak throughput, and server requirements are determined.

3.1 *CarbonStream* Overview

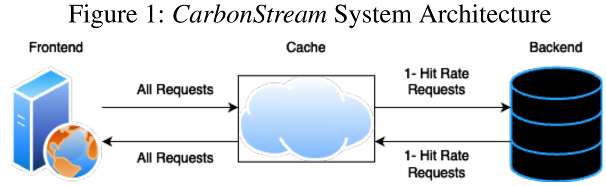
The primary objective of *CarbonStream* is to estimate the embodied carbon costs of different storage technologies: solid-state drives (SSDs), hard disk drives (HDDs), tape, and glass-based storage under typical data center workload conditions. *CarbonStream* accounts for the entire lifecycle of each storage medium, from manufacturing and deployment to operation and eventual disposal. Integrating both operational and embodied carbon costs provides a comprehensive assessment of each storage technology's environmental impact.

3.1.1 System Architecture

CarbonStream is based on a three-tiered architecture typical of a video streaming platform, which includes the frontend, cache, and backend tiers. Each tier consists of a group of servers that work together to handle requests. *CarbonStream* assumes that each server has exactly one storage device. The three tiers are described below:

- **Frontend Tier:** The frontend servers are responsible for handling incoming data requests from users or applications. These servers process the initial request and route it to the cache or backend tiers based on availability and data location. The frontend can be configured with either DRAM or SSD-based servers, depending on the workload demands.
- **Cache Tier:** The cache tier serves as an intermediary storage layer that holds frequently accessed data to reduce the load on the backend storage and decrease latency. The cache tier can be configured using either DRAM or SSDs, providing flexibility in terms of performance, capacity, and cost. DRAM offers the fastest access times, while SSDs provide a balance between speed, capacity, and durability.
- **Backend Tier:** The backend tier consists of the main storage infrastructure, which includes SSDs, HDDs, tape, and glass-based storage. This tier is responsible for storing the bulk of the data, particularly data that is less frequently accessed. When a cache miss occurs, the data is retrieved from the backend storage, which generally invokes a higher latency than the cache tier.

Figure 1: *CarbonStream* System Architecture



3.1.2 Hardware Configurations

CarbonStream simulates data center environments using various storage technologies, each configured according to industry standards and best practices. The storage media considered in this study include:

- **DRAM**
- **Solid-State Drives (SSDs)**
- **Hard Disk Drives (HDDs)**
- **Tape Storage**
- **Glass-Based Storage**

In addition to these storage options, the frontend and cache tiers can be configured with either DRAM or SSDs, depending on the specific requirements of the workload and the SLO parameters.

3.2 SLO Parameters

The Service Level Objectives (SLOs) are critical parameters that define the performance and reliability targets for the data center system. In this model, the SLO parameters guide the configuration of the storage infrastructure to ensure that the system meets the required levels of latency and throughput, which are crucial for maintaining the quality of service.

The key SLO parameters used in *CarbonStream* consist of:

- **Latency Requirement (SLO Latency):** This parameter specifies the maximum allowable end-to-end latency for data requests within the system. It includes the time taken for a request to traverse from the frontend to the backend, accounting for cache hits and misses, as well as network and processing delays. The SLO latency ensures that data is delivered to the end-user or application within an acceptable timeframe.
- **Throughput Requirement (SLO Throughput):** This parameter defines the required system throughput, measured in requests per second. It represents the number of data requests the system must handle per unit time to meet operational demands. The SLO throughput is used to determine the cache hit rate, as well as the number of servers needed in each tier.

3.3 Metrics and Inputs

CarbonStream evaluates each storage technology using a range of metrics to capture the full scope of its carbon impact. These metrics include:

- **Embodied Carbon Cost:** The total greenhouse gas emissions associated with the production, transportation, installation, and disposal of the storage media. This metric accounts for the carbon footprint of the entire lifecycle of the storage devices.
- **Operational Carbon Cost:** The carbon emissions generated during the operation of the storage devices. This includes the energy consumed during read/write operations, as well as the energy required to keep the devices idle when not in use. To calculate these costs, we assumed that approximately 0.5 kg of CO2 is needed to generate one KWh. This translates to 1.39×10^{-7} kg CO2 per watt-second. Since most hardware manufacturers provide the power usage of a device, we can use these estimates to calculate the total operational carbon value. (Note: for glass storage, we had to make a rough estimate for the power usage as the exact numbers were not published.)
- **Replacement Carbon Cost:** The carbon cost incurred when storage devices are replaced due to wear and tear, technological obsolescence, or other factors. *CarbonStream* assumes that replacement occurs only if the simulation period exceeds the expected lifespan of the hardware. We assume it to be the same value as the embodied carbon cost for simplicity.
- **Total Cost of Ownership (TCO):** The sum of the embodied, operational, and replacement carbon costs over the simulation period. This metric provides a comprehensive view of the environmental impact of each storage technology over its entire lifecycle.

3.4 Calculation of Carbon Costs

CarbonStream calculates the carbon costs using the following detailed methodologies:

3.4.1 Embodied Carbon Cost

Embodied carbon cost is calculated based on the total emissions associated with the production, transportation, and disposal of the storage devices. For each storage technology, the embodied carbon is estimated using lifecycle analysis (LCA) data, which provides emission factors for different materials and manufacturing processes.

$$\text{Embodied Carbon Cost} = \sum(\text{Number of Devices} \times \text{Carbon Intensity per Unit})$$

Where:

- **Number of Devices:** The quantity of each storage device required to meet the workload demands.
- **Carbon Intensity per Unit:** The amount of carbon emissions per device unit, derived from LCA data.

CarbonStream incorporates the size of each device and the total number of devices deployed in the data center, scaling the carbon cost accordingly.

3.4.2 Operational Carbon Cost

Operational carbon cost is calculated by estimating the energy consumption of the storage devices during both active (read/write) operations and idle periods. *CarbonStream* uses the following detailed formulas:

a. Active Operation Cost

$$\begin{aligned}\text{Active Operation Cost} = \sum(&\text{Number of Servers}\times\\ &\text{Active Power Consumption}\times\\ &\text{Carbon Intensity of Energy}\times\\ &\text{Operational Time}\times\\ &\text{Active Time Percentage})\end{aligned}$$

Where:

- **Number of Servers:** The number of servers used.
- **Active Power Consumption:** The amount of power (in W) that the device uses while active.
- **Carbon Intensity of Energy:** The carbon emissions per unit of energy consumed (in kg CO2/watt-second).
- **Operational Time:** The total time (in seconds) the system is running, derived from the workload distribution.
- **Active Time Percentage:** The fraction of the time that the system is actively processing requests.

For each tier (frontend, cache, backend), the operational carbon cost is calculated separately:

- **Frontend Active Operation Cost:**

$$\begin{aligned}&\text{Frontend Active Operation Cost} =\\ &\text{Number of Frontend Servers}\times\\ &\text{Frontend Active Power Consumption}\times\\ &\text{Carbon Intensity}\times\\ &\text{Operational Time}\times\\ &\text{Active Time Percentage}\end{aligned}$$

- **Cache Active Operation Cost:**

$$\begin{aligned}&\text{Cache Active Operation Cost} =\\ &\text{Number of Cache Servers}\times\\ &\text{Cache Active Power Consumption}\times\\ &\text{Carbon Intensity}\times\\ &\text{Operational Time}\times\\ &\text{Active Time Percentage}\end{aligned}$$

- **Backend Active Operation Cost:**

$$\begin{aligned}&\text{Backend Active Operation Cost} =\\ &\text{Number of Backend Servers}\times\\ &\text{Backend Active Power Consumption}\times\\ &\text{Carbon Intensity}\times\\ &\text{Operational Time}\times\\ &\text{Active Time Percentage}\end{aligned}$$

b. Idle Operation Cost The idle operation cost is calculated for the periods when the devices are powered on but not actively processing data:

$$\begin{aligned}\text{Idle Operation Cost} = \sum(&\text{Number of Servers}\times\\ &\text{Idle Power Consumption}\times\\ &\text{Carbon Intensity of Energy}\times\\ &\text{Operational Time}\times\\ &\text{Idle Time Percentage})\end{aligned}$$

Where:

- **Number of Servers:** The number of servers used.
- **Idle Power Consumption:** The amount of power (in W) that the device uses when idling.
- **Carbon Intensity of Energy:** The carbon emissions per unit of energy consumed (in kg CO2/watt-second).
- **Operational Time:** The total time (in seconds) the system is running, derived from the workload distribution.
- **Idle Time Percentage:** The fraction of the time that the system is idle.

For each tier:

- **Frontend Idle Operation Cost:**

$$\begin{aligned}&\text{Frontend Idle Operation Cost} =\\ &\text{Number of Frontend Servers}\times\\ &\text{Frontend Idle Power Consumption}\times\\ &\text{Carbon Intensity}\times\\ &\text{Operational Time}\times\\ &\text{Idle Time Percentage}\end{aligned}$$

- **Cache Idle Operation Cost:**

$$\begin{aligned}&\text{Cache Idle Operation Cost} =\\ &\text{Number of Cache Servers}\times\\ &\text{Cache Idle Power Consumption}\times\\ &\text{Carbon Intensity}\times\\ &\text{Operational Time}\times\\ &\text{Idle Time Percentage}\end{aligned}$$

- **Backend Idle Operation Cost:**

$$\begin{aligned}\text{Backend Idle Operation Cost} = \\ \text{Number of Backend Servers} \times \\ \text{Backend Idle Power Consumption} \times \\ \text{Carbon Intensity} \times \\ \text{Operational Time} \times \\ \text{Idle Time Percentage}\end{aligned}$$

c. Total Operational Carbon Cost The total operational carbon cost is then the sum of the active and idle costs across all tiers:

$$\begin{aligned}\text{Total Operational Carbon Cost} = \\ \text{Frontend Active Cost} + \text{Frontend Idle Cost} + \\ \text{Cache Active Cost} + \text{Cache Idle Cost} + \\ \text{Backend Active Cost} + \text{Backend Idle Cost}\end{aligned}$$

3.4.3 Replacement Carbon Cost

Replacement carbon cost is incurred when storage devices are replaced due to reaching the end of their operational lifespan. This cost is only applied if the simulation period exceeds the expected lifespan of the device:

$$\begin{aligned}\text{Replacement Carbon Cost} = \sum(\text{Number of Replacements} \times \\ \text{Embodied Carbon Cost per Device})\end{aligned}$$

Where:

- **Number of Replacements:** The total number of times a device is replaced during the simulation period.
- **Embodied Carbon Cost per Device:** The carbon cost of producing a single device, as calculated in the embodied carbon cost section.

CarbonStream checks the simulation duration against the expected lifespan of each device and calculates the replacement cost only if necessary.

3.5 Calculation of Average Latency and Peak Throughput

3.5.1 Average Latency

Average latency is calculated by considering the latency contributions from the frontend, cache, and backend tiers, as well as the network and processing latencies. The calculation is influenced by the SLO parameters provided to *CarbonStream*, particularly the latency requirement:

$$\begin{aligned}\text{Average Latency} = \\ \text{Frontend Latency} + \text{Cache Hit Rate} \times \\ \text{Cache Latency} + (1 - \text{Cache Hit Rate}) \times \\ (\text{Cache Latency} + \text{Backend Latency}) + \\ \text{Network Latency} + \text{Processing Latency}\end{aligned}$$

Where:

- **Frontend Latency:** The latency introduced by the frontend servers.
- **Cache Hit Rate:** The probability that the cache will serve a data request.
- **Cache Latency:** The latency introduced by the cache servers.
- **Backend Latency:** The latency introduced by the backend servers in case of a cache miss.
- **Network Latency:** The latency introduced by the network infrastructure.
- **Processing Latency:** The latency introduced by the processing of data on the server.

This formula accounts for both the cases where the cache serves data and where a cache miss leads to a backend request. The SLO latency requirement guides the configuration of the system to ensure that the average latency remains within acceptable limits.

3.5.2 Peak Throughput

Peak throughput is calculated as the minimum of the total throughput capabilities of the frontend, cache, and backend tiers, ensuring that the system meets the SLO throughput requirement:

$$\begin{aligned}\text{Peak Throughput} = \min(\text{Frontend Total Throughput}, \\ \text{Cache Total Throughput}, \\ \text{Backend Total Throughput})\end{aligned}$$

Where:

- **Frontend Total Throughput:** The total throughput of the frontend servers, calculated as the throughput per server multiplied by the number of frontend servers.
- **Cache Total Throughput:** The total throughput of the cache servers, calculated similarly.
- **Backend Total Throughput:** The total throughput of the backend servers, calculated similarly.

Each tier's total throughput is determined by:

$$\text{Total Throughput} = \text{Throughput per Server} \times \text{Number of Servers}$$

The peak throughput of the entire system is constrained by the tier with the lowest total throughput, as this tier represents the bottleneck in the data processing pipeline. The system is configured to ensure that the peak throughput aligns with the SLO throughput requirement.

3.6 Calculation of the Number of Servers Needed

The number of servers required in each tier is determined based on the throughput requirement. It is calculated as:

$$\text{Number of Servers} = \left\lceil \frac{\text{Desired Throughput}}{\text{Throughput per Server}} \right\rceil$$

Where:

- **Desired Throughput:** The required system throughput, as specified by the SLO.
- **Throughput per Server:** The throughput capacity of a single server in the specific tier.

This ensures that the system can process the required number of requests per second without exceeding the throughput capacity of any tier.

3.7 Calculation of the Cache Hit Rate

The cache hit rate is a critical factor in determining the efficiency of the caching layer within the data center's storage hierarchy. It directly influences the average latency, as well as the load on both the cache and backend storage systems. In this model, the cache hit rate is calculated based on the size of the cache, the number of cache servers deployed, the total number of videos or data objects stored in the system, and the SLO (Service Level Objective) throughput provided to *CarbonStream*.

3.7.1 Definition

The cache hit rate represents the probability that a data request (e.g., a read operation) will be served directly from the cache rather than having to be fetched from the backend storage. A higher cache hit rate implies that more requests are being satisfied by the cache, leading to lower latency and reduced load on the backend systems.

3.7.2 Assumptions and Considerations

Several assumptions are made in this calculation:

- **Uniform Access Pattern:** It is assumed that all data objects have an equal probability of being accessed, meaning the access pattern is uniform. This simplifies the calculation but may not fully represent real-world scenarios where certain data might be more frequently accessed.
- **Cache Eviction Policy:** *CarbonStream* assumes that the cache uses an efficient eviction policy (e.g., Least Recently Used - LRU) to maximize the cache hit rate. The specifics of the eviction policy are not modeled directly but are implicitly assumed to be optimal.
- **Fixed Data Size:** *CarbonStream* assumes that the total data size remains constant during the simulation, meaning no significant increase in the number of videos or data objects over time.
- **SLO Throughput Adherence:** The number of cache servers is adjusted to ensure that the cache hit rate is sufficient to meet the SLO required throughput.

3.7.3 Calculation Formula

The cache hit rate is calculated using the following formula:

$$\text{Cache Hit Rate} = \frac{\text{Total Cache Size}}{\text{Total Data Size}}$$

Where:

- **Total Cache Size:** The combined storage capacity of all cache servers in the system.
- **Total Data Size:** The total size of all data objects stored in the system (e.g., the total number of videos or other data units).

The total cache size is determined by the number of cache servers and the storage capacity of each server:

$$\text{Total Cache Size} = \text{Number of Cache Servers} \times \text{Cache Server Size}$$

Thus, the cache hit rate can be expressed as:

$$\text{Cache Hit Rate} = \frac{\text{Number of Cache Servers} \times \text{Cache Server Size}}{\text{Total Data Size}}$$

3.7.4 Impact of the Hit Rate on System Performance

The calculated cache hit rate is used to determine the average latency and overall system performance. A higher cache hit rate results in more requests being served from the cache, which reduces the average latency and decreases the load on the backend storage systems. Conversely, a lower cache hit rate increases the likelihood of cache misses, leading to higher latency and greater reliance on backend storage.

4 Evaluation

In this section, we present the results of our simulation model, which evaluates the total cost of ownership (TCO) of carbon across different storage technologies in a video streaming platform simulator.

4.1 Model Implementation

CarbonStream is implemented in Python, leveraging custom algorithms to estimate the carbon costs associated with each storage technology. *CarbonStream* allows for flexibility in configuring the parameters for each storage medium, enabling a wide range of scenarios to be tested.

The simulation runs over a predefined period, 10 years by default, to capture the long-term impacts of embodied and operational carbon costs. During each simulation run, *CarbonStream* tracks the energy consumption, device replacements, latency, throughput, and overall carbon footprint, producing detailed output data that is subsequently analyzed to determine the TCO of each storage technology.

The system is assumed to store 10 Billion GB (10 EB) by default. This value is used to calculate the cache hit rate.

4.2 System Hardware

To provide a realistic and detailed analysis of the embodied carbon costs and operational efficiency of various storage technologies, this study focuses on specific, widely recognized hardware models representative of the current state-of-the-art in data storage. The selected hardware includes:

4.2.1 DRAM

DRAM is utilized in the frontend and cache tier to provide the highest possible speed for frequently accessed data. It is characterized by very low latency and high throughput, making it suitable for applications where performance is critical.

- **Capacity:** 4.4 TB
- **Latency:** 0.00001 ms (10 ns)
- **Throughput:** 20,000 MB/s
- **Embodied Carbon Cost:** $\sim$ 0.31 kg CO2e/GB [13] [14]
- **Power Consumption:** 2560 W ($\sim$2.5 kW)
- **Lifespan:** 10 years

4.2.2 Solid-State Drive (SSD) - Samsung PM9A3

The Samsung PM9A3 is a high-performance NVMe SSD designed for data centers [17]. It offers significant advantages in terms of speed and energy efficiency, with high sequential read and write speeds, and a low power consumption profile. The PM9A3 is widely used in performance-critical environments where rapid data access and high IOPS (Input/Output Operations Per Second) are essential. Its key specifications include:

- **Capacity:** 3.84 TB
- **Latency:** $\sim$ 0.08 ms
- **Throughput (Read):** 6,900 MB/s
- **Throughput (Write):** 4,100 MB/s
- **Embodied Carbon Cost:** $\sim$ 0.16 kg CO2e/GB [20]
- **Power Consumption:** 11 W read, 13.5 W write, 3.5 W idle
- **Lifespan:** 5 years

4.2.3 Hard Disk Drive (HDD) - Seagate Exos X18

The Seagate Exos X18 is a high-capacity enterprise HDD designed for bulk data storage in data centers [18]. It provides a balance between capacity, performance, and reliability, making it suitable for archival and nearline storage. The Exos X18 is known for its durability and relatively low operational power consumption for its class. Key specifications include:

- **Capacity:** 18 TB
- **Latency:** $\sim$ 4.16 ms
- **Throughput:** 270 MB/s
- **Embodied Carbon Cost:** $\sim$ 0.0017 kg CO2e/GB
- **Power Consumption:** 9.5 W active, 5.3 W idle
- **Lifespan:** 5 years

4.2.4 Tape Storage - Fujifilm LTO Ultrium 9

The Fujifilm LTO Ultrium 9 represents the latest in tape storage technology, offering significant capacity and long-term durability with extremely low operational energy requirements [10]. It is primarily used for archival purposes, where data is written infrequently but stored securely for long durations. Key specifications include:

- **Capacity:** 18 TB native, 45 TB compressed
- **Latency:** $\sim$ 10000 ms
- **Throughput:** 400 MB/s
- **Embodied Carbon Cost:** $\sim$ 0.00042 kg CO2e/GB [4]
- **Power Consumption:** 0.26 W active, 0 W idle
- **Lifespan:** 30 years

4.2.5 Glass-Based Storage - Project Silica

Project Silica is an emerging technology developed by Microsoft, which uses quartz glass as a storage medium [3]. This technology promises to provide highly durable storage with an exceptionally long lifespan and low environmental impact. Although still experimental, Project Silica is included in this study to explore its potential as a sustainable alternative to traditional storage media. Key (experimental) specifications include:

- **Capacity:** Up to 7 TB
- **Latency:** $\sim$ 2000 ms
- **Throughput:** 210 MB/s
- **Embodied Carbon Cost:** $\sim$ 0.0001 kg CO2e/GB
- **Power Consumption:** 0.13 W active, 0 W idle
- **Lifespan:** 100 years

The specific configurations chosen for the frontend, cache, and backend tiers allow *CarbonStream* to simulate a variety of scenarios, providing insights into the trade-offs between performance, cost, and environmental impact.

4.3 Tests

We ran several tests with varying parameters to get carbon cost estimates for the various hardware configurations.

In figures 2 and 3, we are simulating with a latency of 10 ms and a throughput of 10 req/s. The independent variable here is the duration. In the first one, we operate the system for a period of one year, and in the second, it is for 10 years. We can see from the graphs that in the 1-year test, none of the hardware needed to be replaced. In the 10-year test, all but two configurations required at least some hardware to be replaced. Another statistic worth noting is that the operational cost significantly dominates the embodied cost for most of the configurations. In this case, the differences in hardware performance are almost negligible, so picking the configuration with the lowest operational cost would be the best choice. We can see that the configuration consisting of an SSD frontend, SSD cache, and glass backend results in the lowest total carbon cost. Swapping glass for tape results in a slightly higher total cost, while using SSDs or HDDs leads to a significantly higher cost.

In Figures 4 and 5, we are now simulating with a throughput of 10000000 req/s, with all other variables remaining unchanged from the previous test. We notice that the embodied cost component is more variable and a larger fraction of the total cost than in the previous test. This demonstrates that the specific workload that the server is running is very important.

Figure 2: 1-year simulation with SLO Latency of 10 ms and Throughput of 10 req/s.

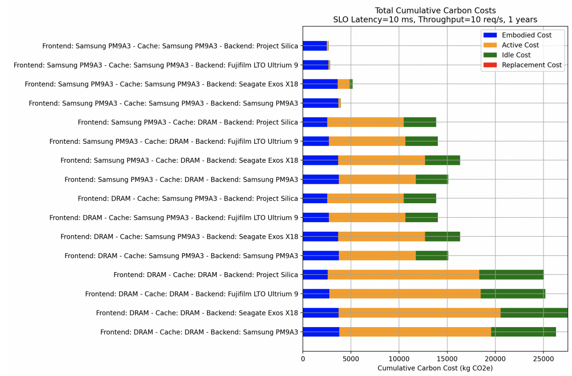
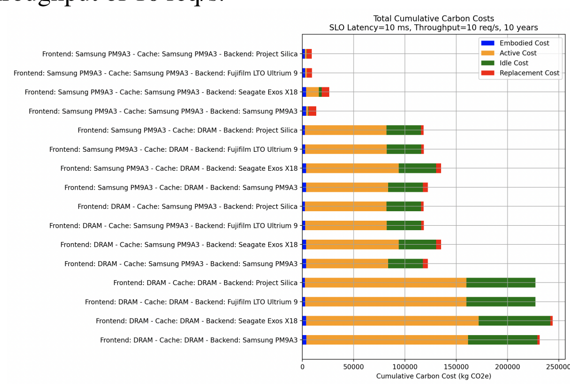


Figure 3: 10-year simulation with SLO Latency of 10 ms and Throughput of 10 req/s.



4.4 Comparison of Storage Technologies

The key metrics used to evaluate the storage technologies include embodied carbon cost, operational carbon cost, replacement carbon cost, and total carbon cost. These metrics are assessed under different workload conditions and service level objectives (SLOs) to determine the most carbon-efficient storage solution.

4.4.1 Embodied Carbon Cost

- DRAM had the highest embodied cost per device, but due to its high performance, fewer servers were needed compared to SSDs, reducing the overall cost.
- SSDs, while offering high performance, have a significantly higher embodied carbon cost due to the complex manufacturing processes involved in producing flash memory.
- HDDs and tape storage offer lower embodied carbon costs compared to SSDs, with tape being particularly efficient in terms of long-term archival storage. However, since both HDDs and tape have a much lower throughput

Figure 4: 1-year simulation with SLO Latency of 10 ms and Throughput of 10000000 req/s.

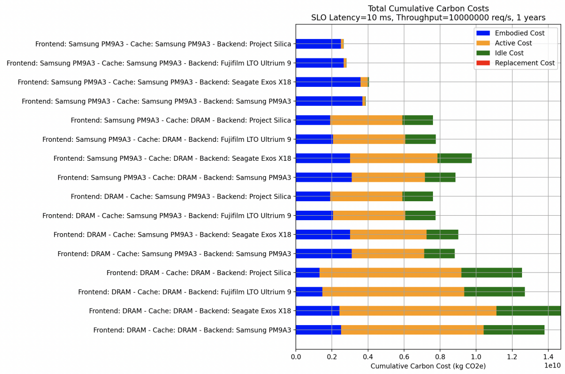
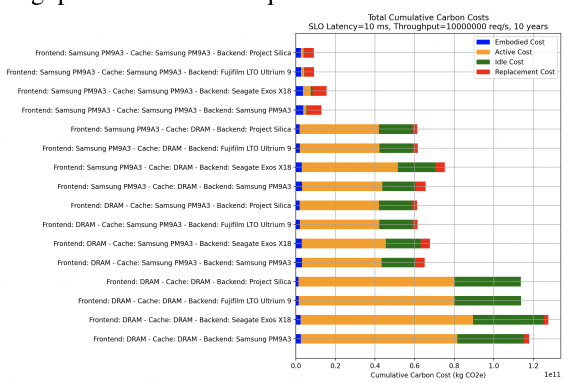


Figure 5: 10-year simulation with SLO Latency of 10 ms and Throughput of 10000000 req/s.



than SSDs, more servers are needed to meet the SLO throughput requirement, leading to a higher total embodied cost.

- Glass-based storage has the lowest embodied carbon cost due to the minimal material requirements and longevity of the medium.

4.4.2 Operational Carbon Cost

- DRAM had the best performance at the expense of having the highest operational cost.
- SSDs offer a balance between operational cost and performance, with the best performance amongst the storage devices at the cost of higher operational costs compared to tape and glass.
- HDDs had the second-highest operational cost in addition to being outperformed by SSDs.
- Tape and glass-based storage, with near-zero operational energy consumption when idle, provide the most efficient solution for long-term data storage.

4.4.3 Replacement Carbon Cost

- DRAM had the highest replacement cost per device, but due to its longer lifespan than SSDs, the overall cost was lower.
- SSDs and HDDs have higher replacement carbon costs, with HDDs being more frequently replaced due to their mechanical components.
- Tape storage, while having a longer lifespan than HDDs, still requires periodic replacement, contributing to its replacement carbon cost.
- Glass-based storage, with its exceptional durability, incurs the lowest replacement carbon cost, as the need for replacements is minimal.

4.5 Impact of Frontend and Cache Configurations

The evaluation also considers the impact of different frontend and cache configurations (DRAM vs. SSDs) on overall system performance and carbon efficiency.

- DRAM in the frontend and cache tiers provides the highest performance and the lowest latency, at the expense of higher operational costs.
- SSDs, while slower than DRAM, offer a more cost-effective solution with lower embodied carbon costs, making it suitable for less latency-sensitive but still performance-critical workloads.

4.6 Total Carbon Cost Analysis

The total carbon cost, encompassing embodied, operational, and replacement costs, provides a comprehensive measure of each storage technology's environmental impact. The results indicate that:

- DRAM, while the most performant, incur the highest embodied carbon cost. This became less important as the duration of the simulation increased.
- SSDs, while the most performant, incur the second-highest embodied carbon cost. This also became less important as the duration of the simulation increased.
- HDDs, despite having a lower embodied carbon cost than SSDs, had the highest total carbon usage out of all of the storage devices that were compared.
- Tape storage, with its low operational and embodied carbon costs, remains a strong contender for archival storage solutions, particularly in scenarios where data access is infrequent.

- Glass-based storage, despite being an emerging technology, shows significant potential for reducing total carbon costs in data centers, especially when combined with SSDs in the frontend and cache tiers.

5 Conclusion

In this study, we investigated the total cost of ownership (TCO) of carbon for various storage technologies used in data centers. By developing and utilizing a custom simulation model, we compared the carbon impact of solid-state drives (SSDs), hard disk drives (HDDs), tape, and glass-based storage, with additional analysis of DRAM and SSDs in the frontend and cache tiers.

Our analysis revealed that glass-based storage, an emerging technology, holds significant promise for reducing the carbon footprint of data center operations. Glass storage demonstrated the lowest total carbon cost, making it a highly sustainable choice for performance-intensive workloads. This finding supports our thesis that glass-based storage can potentially replace existing media in data centers by offering a lower total carbon burden.

Tape storage also emerged as a highly efficient solution for long-term archival storage, thanks to its low operational and embodied carbon costs. Despite its slower performance, tape remains a valuable option for scenarios where data is infrequently accessed.

SSDs, while providing the best performance, were found to have the highest embodied carbon cost. This underscores the environmental trade-offs associated with high-performance storage solutions.

Overall, the results of this study highlight the importance of carefully selecting storage technologies and system configurations to optimize both performance and sustainability in data center operations. The findings demonstrate that it is possible to significantly reduce the carbon footprint of data centers by adopting emerging technologies like glass-based storage and making informed decisions about cache and server configurations.

6 Future Work

While this study provides valuable insights into the carbon costs of various storage technologies, there are several avenues for future research that could further enhance the sustainability and efficiency of data center operations.

One potential area of investigation is the feasibility of incorporating data compression into the model. By testing different compression algorithms, we could determine where the best place to deploy compression servers within the three-tiered architecture would be. This could reduce the overall data footprint, thereby lowering storage requirements and potentially reducing carbon costs.

Another important direction for future research involves exploring variable data access patterns. By modeling different access patterns, we can better understand how data placement strategies impact performance and carbon costs. Additionally, investigating redundancy management strategies will be crucial to ensure that data is protected from drive failures while minimizing the amount of data duplication required. Effective redundancy management would also need to support the scalability of the system to meet Service Level Objective (SLO) requirements.

Moreover, future studies could look into optimizing data placement strategies, particularly in the context of ensuring that data is placed on the most appropriate storage medium given its access frequency and importance. By optimizing data placement, we can further reduce the operational costs and improve the overall efficiency of data centers.

Another significant area of future research involves studying the impact of fluctuating carbon intensity in energy grids on operational carbon costs. Energy grids often have varying carbon intensities depending on factors such as time of day, season, and the mix of renewable versus non-renewable energy sources available at a given time. By incorporating dynamic carbon intensity models into the simulation, we can assess how scheduling data center workloads or shifting storage access patterns to align with lower-carbon-intensity periods could further reduce the overall carbon footprint.

Finally, as glass-based storage technology matures, future work could explore its long-term durability and scalability in production environments. This research would help validate the potential of glass storage as a mainstream solution for sustainable data storage.

These future research directions aim to build on the findings of this study, offering actionable insights to drive innovation and sustainability in data center operations. By addressing these challenges, this research has the potential to shape the next generation of environmentally conscious data centers. Ultimately, these efforts align with the broader goal of reducing the environmental impact of the digital economy while maintaining the performance and reliability required to support its continued growth.

References

[1] ACUN ET AL. Carbon Explorer: A Holistic Framework for Designing Carbon Aware Datacenters. In *ASPLOS 2023: Proceedings of the 28th ACM International Conference on Architectural Support for Programming Languages and Operating Systems, Volume 2* (March 2023), pp. 118–132. https://doi.org/10.1145/3575693.3575754.

[2] ANDERSON ET AL. Glass: A New Media for a New Era? In *10th USENIX Workshop on Hot Topics in Storage and File Systems (HotStorage 18)* (July 2018). https://www.usenix.org/conference/hotstorage18/presentation/anderson.

[3] ANDERSON ET AL. Project Silica: Towards Sustainable Cloud Archival Storage in Glass. In *The 29th ACM Symposium on Operating Systems Principles* (October 2023), pp. 166–181. https://dl.acm.org/doi/pdf/10.1145/3600006.3613208.

[4] BRAD JOHNS. Improving Information Technology Sustainability with Modern Tape Storage, July 2021. https://asset.fujifilm.com/www/sg/files/2021-09/d9c014a35ae86bdc41d78abf6e693bb1/Improving_IT_Sustainability_with_Tape_BJC.pdf.

[5] BREVAN REYHER. Embodied Carbon Considerations For Data Centers, January 2022. https://www.missioncriticalmagazine.com/ext/resources/whitepapers/2022/Embodied-Carbon-White-Paper.pdf.

[6] CHRIS MELLOR. Tape is low cost and a low carbon storage winner, July 2022. https://blocksandfiles.com/2022/07/11/tape-is-low-cost-and-a-low-carbon-storage-winner/.

[7] CHRIS MELLOR. HDDs may be greener than SSDs, August 2023. https://blocksandfiles.com/2023/08/18/hdds-may-be-greener-than-ssds/.

[8] DAVID ET AL. Memory Power Management via Dynamic Voltage/Frequency Scaling. In *ICAC '11: Proceedings of the 8th ACM international conference on Autonomic computing* (June 2011), pp. 31–40. https://dl.acm.org/doi/pdf/10.1145/1998582.1998590.

[9] EPA. What is Embodied Carbon?, July 2024. https://www.epa.gov/greenerproducts/what-embodied-carbon.

[10] FUJIFILM. LTO Ultrium 9 Sell Sheet, 2021. https://asset.fujifilm.com/www/us/files/2024-01/ce72cf783970aa0d05d4463e4febcb62/FB_LTO9_SellSheet_V1.pdf.

[11] GUPTA ET AL. ACT: designing sustainable computer systems with an architectural carbon modeling tool. In *Proceedings of the 49th Annual International Symposium on Computer Architecture* (June 2022), pp. 784–799. https://ugupta.com/files/Gupta_ISCA2022_ACT.pdf.

[12] GUPTA ET AL. Chasing Carbon: The Elusive Environmental Footprint of Computing. In *IEEE Micro, Volume 42, Issue 4* (July 2022), pp. 37–47. https://doi.org/10.1109/MM.2022.3163226.

[13] KOHLER ET AL. Carbon-Aware Memory Placement, July 2023. https://dl.acm.org/doi/pdf/10.1145/3604930.3605714.

[14] LI ET AL. Toward Sustainable HPC: Carbon Footprint Estimation and Environmental Implications of HPC Systems, November 2023. https://arxiv.org/pdf/2306.13177.

[15] MICROSOFT. Sealed in glass, 2024. https://unlocked.microsoft.com/sealed-in-glass/.

[16] RADOVANOVIC ET AL. Carbon-Aware Computing for Datacenters, June 2021. https://arxiv.org/pdf/2106.11750.

[17] SAMSUNG. PM9A3 Whitepaper, August 2021. https://download.semiconductor.samsung.com/resources/white-paper/PM9A3_SSD_Whitepaper_230327_2.pdf.

[18] SEAGATE. EXOS X18 Sustainability Report, 2021. https://www.seagate.com/esg/planet/product-sustainability/exos-x18-sustainability-report/.

[19] SOUZA ET AL. Ecovisor: A Virtual Energy System for Carbon-Efficient Applications. In *ASPLOS 2023: Proceedings of the 28th ACM International Conference on Architectural Support for Programming Languages and Operating Systems, Volume 2* (March 2023), pp. 252–265. https://dl.acm.org/doi/pdf/10.1145/3575693.3575709.

[20] SWAMIT TANNU AND PRASHANT J. NAIR. The Dirty Secret of SSDs: Embodied Carbon. In *SIGENERGY Energy Inform. Rev. 3, 3 (October 2023)* (October 2023), pp. 4–9. https://arxiv.org/pdf/2207.10793.