

# CaRE: Towards Carbon and Resource Efficient Orchestration at the Cloud-Edge Continuum

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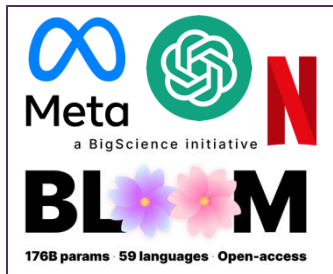
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# The problem of Carbon Emissions Reduction

Challenge: Increased Carbon Emissions due to **exponential growth** of Computing.



Key drivers:

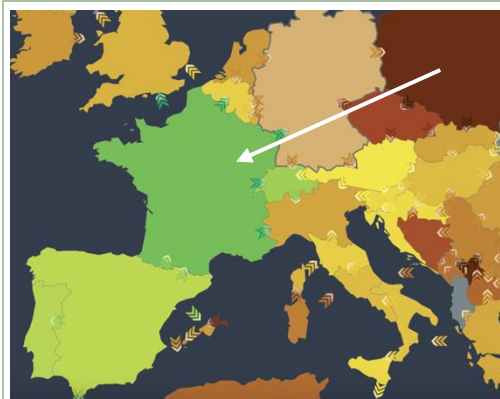
- ML applications
- Generative AI
- Video streaming



AI Model	Carbon Impact of Training*	Real-word equivalent example
GPT-3	500 metric tons of CO <sub>2</sub> eq. <sup>[1]</sup>	500 round-trip flights from Madrid to New York for one passenger.
GPT-4	12,456 - 14,994 metric tons CO <sub>2</sub> eq (estimated). <sup>[2]</sup>	50-60 fully loaded Boeing 747 flights.

Solution: **Spatial** and **Temporal** Workload Shifting.

\*Training only accounts for 43% of lifecycle carbon emissions. <sup>[1]</sup>



[3]  Spatial Shifting

Fossil-fuel-heavy regions


Workload Migration

Greener areas 



Temporal Shifting



 Pause with no strong latency requirements (e.g., batch jobs)

 Resume when green energy available.

**Sources** [1]: Beyond Efficiency: Scaling AI Sustainably

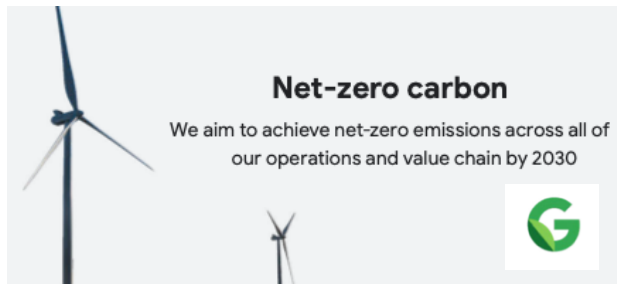
[2]: <https://towardsdatascience.com/the-carbon-footprint-of-gpt-4-d6c676eb21ae>

<https://app.electricitymaps.com/map/7zh>

# The problem of Carbon Emissions Reduction



During the last 2 years existing systems are **redesigned** with the end goal of **reducing carbon emissions**.



## Carbon negative

Our carbon negative commitment includes three primary areas: reducing carbon emissions, increasing use of carbon-free electricity, and carbon removal. We made meaningful progress on carbon-free electricity and carbon removal in FY23. Microsoft has taken a first-mover approach to supporting **carbon-free electricity** infrastructure, making long-term investments to bring more carbon-free electricity onto the grids where we operate.



## Going Green for Less Green: Optimizing the Cost of Reducing Cloud Carbon Emissions

ASPLOS '24

## Ecovisor: A Virtual Energy System for Carbon-Efficient Applications

ASPLOS '23

## Carbon Explorer: A Holistic Framework for Designing Carbon Aware Datacenters



## CARIBOU: Fine-Grained Geospatial Shifting of Serverless Applications for Sustainability

SOSP '24

# The problem of Carbon Emissions Reduction



**Solved?**



**Well... Not quite.**



# Implications of CO<sub>2</sub> reductions on other aspects

Problem: **Resource**, **Performance**, and **Cost** are compromised when reducing CO<sub>2</sub>.

## Resource Awareness

Idle!



- Resource Waste
- Energy Inefficiency
- Increased Cost

Temporal Shifting

## Cost Awareness



Spatial Shifting

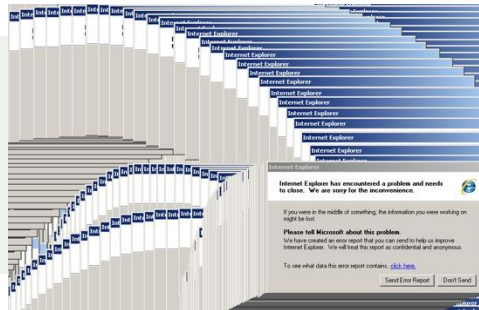
Small national companies need **additional budget** to rent remote resources in greener regions.



## Performance Awareness



Only **specific types** of jobs can be shifted in time.

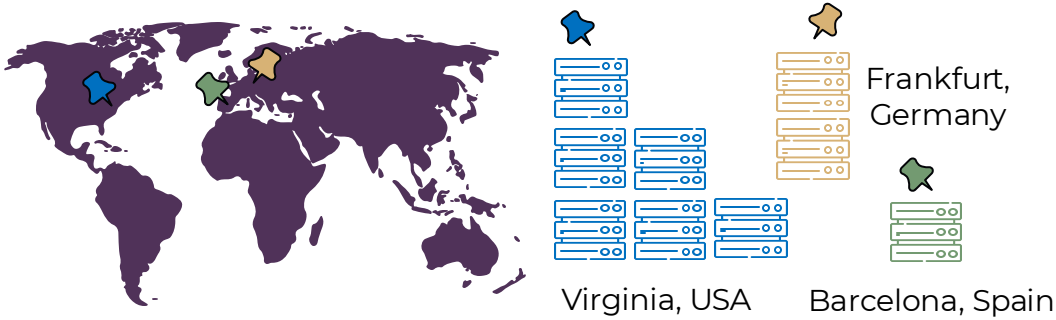


Not all workloads can wait!




**Takeaway:** Optimizing Carbon + Resource + Cost + Performance = Harder than it looks.

# Applications across the Edge-Cloud Continuum




Heterogeneous resources + diverse applications = complex trade-offs

## Real-World Conflicting Requirements

1. Movie Platform Recommendations 

- Not time-sensitive.
- Global platform, resources worldwide.

**Carbon Efficiency Focus**

3. Online Gaming 

- Latency-critical application.
- Carbon efficiency is secondary to user experience.

**Performance Requirements** 

2. Small National Business in Spain 

- Limited local resources.
- Renting resources elsewhere is costly.

**Cost Constraints**

**Takeaway:** Each application across the cloud-edge continuum values carbon, resources, cost, and performance differently.



# Motivation – Preliminary Results

## 1. Experimental Methodology



**Usecase:** Company with entire cloud-edge infrastructure deployed in Spain.

Location	Carbon Intensity
Spain <b>ES</b>	206 gCO <sub>2</sub> eq/kWh
Sweden <b>SE</b>	20 gCO <sub>2</sub> eq/kWh

↓ The lower the better

**Goal:** Quantify the additional **cost (\$)** to rent resources in Sweden to reduce the **carbon footprint**.

## 2. Experimental details

**Applications** (using the Microservices benchmark **DeathStarBench**)

Social Network

24 Microservices

Users send requests to compose posts.

Media streaming

32 Microservices

Movie platform where users can log in and upload movie reviews.

**Workload**



10 minutes

- 1,000 requests to each application
- Time steps follow a Poisson distribution, emulating multiple concurrent users

# Motivation – Preliminary Results

1. Composing and uploading a movie review is **more computationally demanding** than creating a social media post.

Application	AVG Latency
Social Network	9.49 ms
Media Streaming	26.08 ms

2.89x



~10x ~2x

2. Running the applications in Sweden, is a much more **sustainable** solution.



3. *Hosting the media streaming in Sweden will lead to a **higher impact** in sustainability.*



4. **Double the budget** is needed for similar infrastructure in a different country. Users from Spain will connect first to the closest DC → the application runs on both locations.



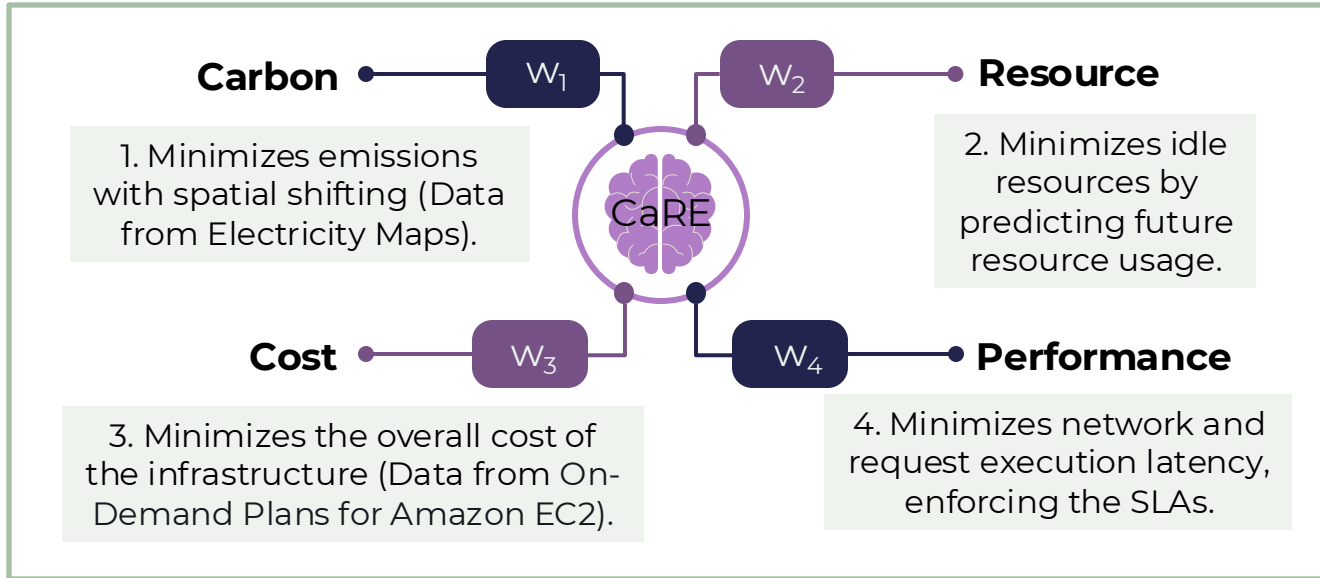
**Takeaway:** Become **greener** → More **money**.  
Choose wisely what to offload!

\*Source: Amazon EC2 On-Demand Pricing. Hourly rate in the eu-south-2 region for Spain, eu-north-1 region for Sweden.

We need an **application-specific solution** for the **carbon – cost trade-off**.



# CaRE: A Carbon and Resource Efficient Orchestrator for the Cloud-Edge Continuum



CaRE **prioritizes** the optimization metrics according to the **specific application requirements** and the user preferences.

Current Application:  
**Microservices**

Future Work:  
Extend to **serverless** applications.



**Takeaway:** CaRE jointly optimizes the **carbon, resource** and **cost** efficiency of the workloads, complying with **SLAs**.

# Challenge – Accurate Resource Usage Prediction

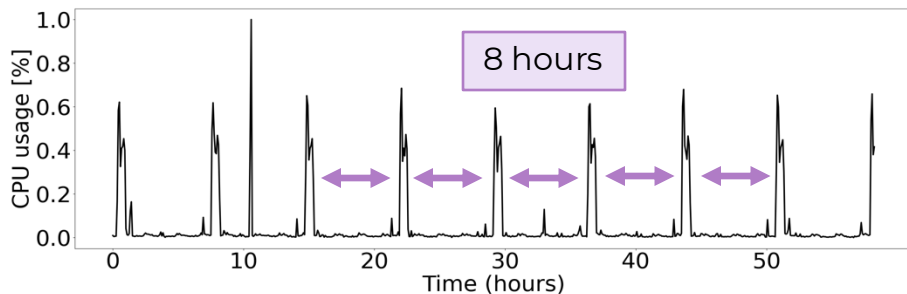
## 1. Proposed Approach: **Persistent Forecast.**

Assume **resource usage repeats itself periodically.**



User behaviours follow predictable cycles.

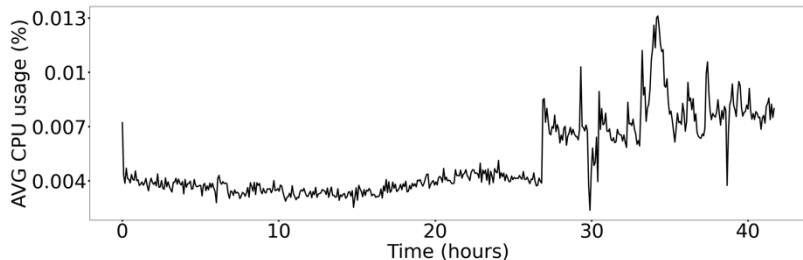
Cloud data is **highly correlated** in time.



Highly **accurate** on cloud data with average prediction error 7%.\*

\* Is Machine Learning Necessary for Cloud Resource Usage Forecasting? SoCC '23. G. Christofidi, K. Papaioannou, T. D. Doudali.

## 2. **Limitations** of the Persistent Forecast – **hard to predict patterns.**



Resource utilization is often **unpredictable**, even when everything is running correctly.

When unexpected usage occurs:

- Lower resource efficiency.
- Potential resource contention.
- Higher carbon footprint.

We deploy **anomaly detection techniques**, to predict highly dynamic resource usage.



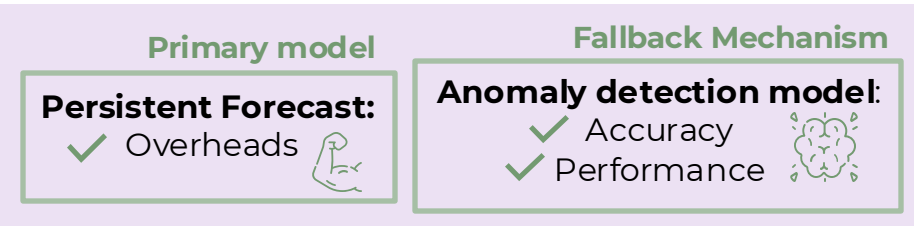
# Proposed Approach for Prediction

## 3. Handling **Anomalies** with a **Two-Model Approach**.

When the persistent forecast accuracy drops below a minimum accuracy threshold, we enter an **anomalous state**.

Fallback Mechanism that predicts:

- **Duration** of the anomaly.
- **Resource usage** during this time.



For the **anomaly detection model** we will explore a variety of ML and non-ML methods commonly used for anomaly detection.

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