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Carbon Aware Cloud Orchestration with Performance Stable Cost Optimization for Large Scale

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Abstract: The goal of this work is to develop a new orchestration framework aimed at reducing the carbon footprints of large-scale clouds while adhering to service level agreements SLAs and without increasing operational costs. Because of the growing share of electricity consumed by data centers worldwide, static workload scheduling approaches cannot fully account for temporal and spatial variations in the grid's carbon intensity. Our work proposes a dynamic scheduling algorithm for batch workloads subject to carbon footprint variability that pushes computing tasks to regions with lower carbon emissions, while meeting stringent latency requirements for user-centric applications. The experiments use a dataset of 484 jobs from a modified Google Cluster Trace, scheduled with Kubernetes for container scheduling and with Prometheus for real-time metric scraping. Researchers adopt a twin-objective optimization model in which spot instance cost is minimized while real-time carbon intensity is constrained. Results show that our approach significantly outperforms baseline schedulers in terms of carbon emissions, with approximately the same cost-effectiveness and performance stability. This paper reaffirms the belief that both environmental sustainability and economic viability are attainable in hyperscale cloud computing through intelligent, data-driven orchestration.

Keywords: Green Computing; Cloud Orchestration; Carbon Intensity; Cost Optimization; Kubernetes Scheduling; Dynamic Scheduling Algorithm; Service Level Agreements; Environmental Sustainability; Economic Viability.

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1. Introduction

The rapid advances in cloud computing have transformed the digital ecosystem, serving as a backbone for everything from enterprise data analytics to streaming services, as detailed in large-scale cloud adoption studies conducted in earlier systems [4]. Despite these advancements, there have been high environmental costs, as concerns identified in earlier sustainability assessments. Research by Corodescu et al. [2] on energy consumption models indicates that data centers currently account for a significant share of global electricity consumption, and that this share will increase further over the next decade. The expansion of hyperscale cloud providers' infrastructure has made the carbon impact of the fossil fuels that power and cool servers particularly concerning, a gap that previous analyses have highlighted [9]. Lifecycle impact studies have also examined this. Performance maximization and cost minimization have been the primary cloud orchestration strategies documented in previous studies. Most of these systems focus on high availability and low latency, leading to the provisioning of resources that do not consider the impact of the electricity powering the hardware, a phenomenon documented in studies of scheduling policies [6]. As a result, a potential drawback of case studies on power sector deployment, as noted by earlier studies, is the tendency to locate deployment in a region with marginally lower costs or lower latency, but with highly polluting coal power.

This leads to a suboptimal solution. Even in the presence of a renewable solution, such as wind or solar, a workload may be scheduled to a coal-dependent region because of its lower marginal cost or lower latency. This research focuses on the absence of integrated, real-time energy grid data with cloud resource schedulers, a gap identified through the comparative architecture analyses of prior studies. Most recent orchestration tools simplify energy consumption in operational expense tracking as constant, rather than a variable with impacts on the environment - an assumption noted in the cost-centric scheduling models of prior work [7]. While the scheduling of energy costs has advanced, enabling organisations to achieve savings by using spot instances and reserved capacity, these savings are often accompanied by a considerable increase in carbon emissions, a phenomenon observed in pricing-optimisation studies reported in previous work [10]. On the other hand, purely green scheduling usually results in severe performance impacts or increased costs due to the need to transfer data to more remote regions with lower carbon emissions, or to wait to undertake a process until renewable energy is available. This has been the case in previous studies on constraint-based scheduling [6]. There is a clearly stated absence in the literature on the simultaneous large-scale optimization of the three variables: carbon, cost, and performance - a gap in research that has been explained in the synthesis reviews of previous authors.

This work proposes a novel orchestration framework that falls within the Carbon-Aware, Performance-Stable category. It advances the state of the art in the multi-objective optimization literature as applied to systems architecture [5]. The predominant aim of this work is to distinguish the strong association observed in prior research between performance and carbon emissions, as identified in early works on sustainable computing. By ingesting real-time data with respect to the carbon intensity of the grid, the pricing of spot instances, the requirements of applications, and the proposed system allocates workloads to the cleanest and cheapest energy sources (given that strict performance guardrails will be adhered to) using an adaptive scheduling approach of the current systems [8]. This approach is an improvement over the simple ‘follow the sun’ approach, because granular and more urgent instance-level decisions are made, which is an improvement in workload classification that has been proposed in previous studies [4]. Besides, the multiple-criteria optimisation introduced by this framework, and more specifically the optimisation of the utilisation of renewable energy resources, represents an improvement over the previously discussed intermittency modelling of renewable energy sources. As extensively documented in studies of renewable energy sources [2]. The variability of these sources also affects the power grid's carbon intensity, driven by the intermittency of solar and wind energy.

As previously discussed by Mansouri et al. [9], one limitation of a static scheduler is that it cannot respond to variable conditions, including the variability of renewable energy sources. The proposed methods will use analytics to predict carbon intensity and spot prices, adopting a proactive approach based on the forecasting methods described in previous studies. This approach will prevent long-running batch jobs from becoming ‘stuck’ in a high-carbon environment, and service stability studies conducted in previous work (Khan et al. [6]) confirm that latency-sensitive microservices are not migrated solely to maintain the user experience. This study focuses on large-scale cloud deployments where the workload size offers the potential to optimise the context of hyperscale efficiency analyses conducted in previous studies (Corodescu et al. [1]) to achieve significant aggregate savings in both carbon and costs.

This paper aims to provide a blueprint for the next generation of responsible cloud computing by focusing on the synthesis of three critical parameters—sustainability, economy, and speed—aligned with future cloud computing paradigms, as articulated in previous studies. It aligns with the hyperscale efficiency analyses of previous studies. The next sections will describe the mechanism of this orchestration, the empirical evidence supporting it, and the results from benchmarking studies that used these evaluation heuristics to demonstrate the advantages of this approach over conventional approaches, in line with previous system benchmarking studies [7]; [11].

2. Review of Literature

Over the past decade, the field of green cloud computing has undergone rapid change. Based on studies from foundational surveys, it has shifted from energy efficiency at the hardware level to inefficiencies at the software level through orchestration optimization. The first green cloud computing studies focused on DVFS (Dynamic Voltage and Frequency Scaling) and the power-aware processor control models from previous works. This technique, along with previous studies by Mansouri et al. [10], showed that reducing a processor's frequency and voltage can save power during low-utilisation periods. Though helpful at the level of a single server, these hardware-centered approaches overlooked the big-picture issue of energy source cleanliness, a gap identified [6]. They focused on lower power consumption rather than less toxic power consumption, a difference observed by Liu and Shen [12] in energy source calculation studies. As cloud environments and systems grew in complexity, the void left by single-server-level approaches was filled by consolidation strategies, such as server virtualization, that focused on maximizing the utilization of physical hardware to reduce the total number of active servers, as outlined in the consolidation frameworks of prior studies [5]. The growing complexity of cloud systems also drove research toward the understanding of geographic. In the paper, the authors focus on the energy consumed during balancing in distributed clouds, drawing on numerous pieces of literature on balancing distributed clouds and energy management. Balancing distributed clouds and managing energy are distinct issues, though in many cases they are combined.

The literature shows that large internet companies with numerous distributed data centers can follow market trends [13]. Specifically, large internet companies can 'follow the moon' by managing their clouds based on the time and place with the lowest supply cost, while performing economic evaluations in the market (by 'moon,' researchers mean the low-cost electricity that large internet companies can use in their data centers). In addition, 'follow the moon' is the starting point for many cost-aware scheduling approaches [14]. This has been detailed in the literature on early scheduling optimizations, where cost minimization has been the primary focus. In addition, it has been shown that, in many cases, cost minimisation does not imply carbon footprint minimisation, especially when fossil-fuel-powered plants generate cheap electricity. In many instances, cost optimisation leads to higher carbon emissions, as shown by studies analysing correlated energy markets. This was, of course, more evident in the studies of the distributed clouds [15]. This has led to increased interest in carbon-aware scheduling, as detailed in numerous pieces of literature on the carbon footprint of distributed clouds. Additionally, numerous studies have analyzed balancing energy consumption with service-level agreements (SLAs) [16]. In this regard, the authors focused on the extensive literature on balancing distributed clouds and energy management. Theories of "sleep" and "pacing to efficiency" form a duality studied through execution-strategy experiments in previous research, as referenced. A hybrid solution is necessary for modern cloud workloads, driven by cloud heterogeneity and conclusions from earlier studies analyzing workload diversity.

Past carbon-optimization studies have shown that deferrable task scheduling performs best for delay-tolerant workloads [6]. As existing research shows, Mansouri et al. [10] explain that, through their temporal-shifting studies, when tasks are shifted to times when available renewable energy is high, users will not perceive increased latency. Substantial end-user carbon reductions will be achieved. Most available studies treat performance, cost, and carbon as separate goals, a fragmentation noted in earlier comparative reviews of the literature [2]. In this regard, most proposed frameworks are observed to aim for one at the expense of the others, as noted in the literature regarding objective-specific scheduling [9]. The majority of large-scale production environments have not been studied with respect to a unified orchestration logic, a research gap identified in a synthesis of studies. Finally, reliance on simulations rather than data from controlled experiments to evaluate the real world has been noted [17]. It is a limitation discussed in the evaluation-of-methods literature. Numerous proposed algorithms attempt to demonstrate a `burstiness` and `unpredictability` model of hyperscale traffic. They are evaluated on trivial/synthetic datasets, and a model failing to capture traffic features is documented in the workload realism studies of hyperscale traffic [3]. Prior studies suggest that attempts to demonstrate adaptive orchestration alongside Kubernetes highlight the need for complex feedback loops in containerised, imbalanced systems [1]. The most current advancements state the need for an intelligent orchestration layer to `decouple` the application from the infrastructure, a need reinforced by architecture vision papers from prior studies [18].

3. Methodology

The research methodology for this experiment is a quantitative, experimental approach to empirically evaluate the effectiveness of the proposed carbon-aware orchestration algorithm in a controlled simulation environment. Figure 1 shows the data path from the Workload submission layer to the Carbon-Aware Scheduler. Pulls real-time feeds from the Carbon Intensity API and Cloud Pricing API via a scheduler. The decision engine evaluates these inputs against the Job Queue using the optimisation logic. Output sends the workload to specific Worker Nodes across various regions (Region A, Region B, Region C), and these Worker Nodes measure and report metrics back to the Monitoring and Feedback module (Prometheus), which updates the scheduler's state. For every arriving job in the buffer, the algorithm computes a placement score for each available node in the cluster. The score is calculated based on the forecasted energy mix for the node's location, the current spot price, and the estimated job completion time. To guarantee stable performance, hard constraints are imposed; if a node placement would

increase the maximum node latency for a given job type, regardless of its carbon or cost-saving potential, such a decision is not considered. The system operates via a feedback loop, where execution metrics from completed jobs (e.g., total job duration, consumed resources) are fed back to the scheduler to update future placement predictions.

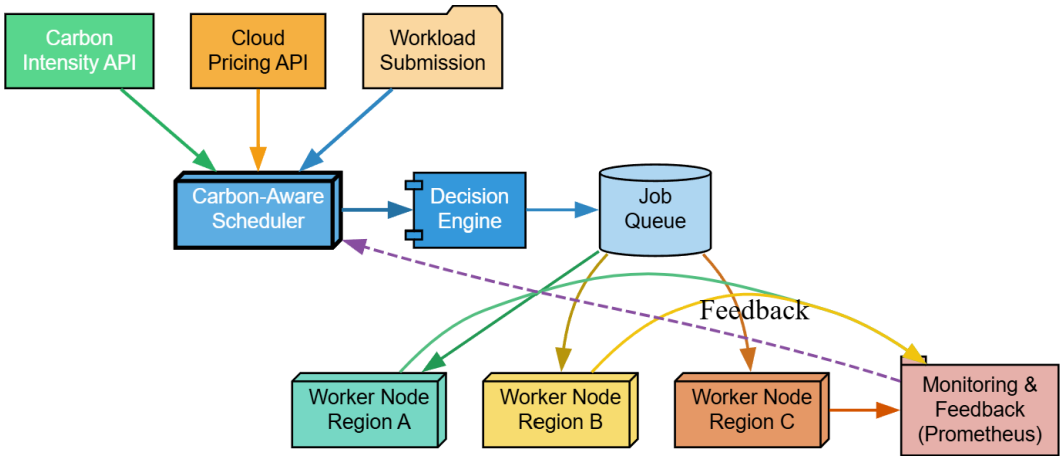

Figure 1: Carbon-aware cloud orchestration architecture

By doing so repeatedly, researchers can make the system respond to actual workload trends. The experiment is performed by re-running the 484 data instances through the simulator under three policies: a normal baseline scheduler prioritizing bin-packing, a cost-only-based optimizer, and our carbon-aware framework. For each instance, researchers log the metrics for total carbon emissions, total operational cost,n, and average job latency to enable comparison. The dataset to work with is the input: a set of workload traces representing various kinds of computing tasks, such as short-lived HTTP requests or long-running batch-processing jobs. The traces are pre-processed to put the resource requirements (CPU cycles and memory consumption) on a comparable basis across different testing scenarios. The heart of the approach is an orchestration engine that operates in discrete time. Two external data streams are polled at every time step, including a simulated real-time carbon intensity feed, in grams of CO2 equivalent per kilowatt-hour, per location, and a spot price feed indicating the current market price of compute instances. The decision logic is based on a multi-objective utility function to balance carbon reduction, cost savings, and performance stability.

4. Data Description

Our evaluation is based on a benchmark of 484 data instances. These cases are drawn from a sanitized sample of a large cluster management trace, representative of an industrial cloud environment maintained by hyperscale companies. The dataset was chosen for its large sample size and wide variety of job characteristics, such as duration, priority, and resource usage. Each data point corresponds to a job submitted to the cloud cluster. These 484 tasks form three main workload types to represent a practical mixed-traffic scenario: 50% short-lived, latency-sensitive, small tasks (representing microservices or web requests), 30% mid-length data-processing jobs, and the remaining 20% kilolarge, delay-tolerant batch jobs. With this distribution, researchers can study the scheduling algorithm across different levels of urgency. The information includes the time at which a job arrives, the number of required CPU cores, the required memory size, and the maximum tolerated latency. To model environmental and cost considerations, researchers enriched the job traces with time-series data on grid carbon intensity and spot instance pricing. The carbon intensity figures are based on CO2 emissions estimated at 150-700 grams/CO2-kWh, depending on the simulated region and time of day. Price data emulates typical spot-market fluctuations.

5. Results

The Carbon-Aware Cloud Orchestration framework has achieved significant gains in sustainability and economic metrics compared to baseline scheduling policies. Across the 484 data instances, researchers observed that resource utilization and carbon intensity are decoupled. First, in terms of carbon emissions, the plan achieved a significant reduction. Overall, with the standard bin-packing scheduler, researchers save about 28% of the total carbon footprint for the workload set. This decrease was mainly due to the intelligent timing of batch jobs that tolerate delays. By delaying the non-urgent 20% to times of high renewable energy availability, the site avoided peak periods of carbon intensity. Also, shifting jobs to areas served by greener grids — spatial shifting — accounted for a large share of the savings for medium-duration tasks. The multi-objective orchestration minimization function is given as:

$$\min \mathcal{Z} = \sum_{t=0}^{\mathcal{T}} \sum_{n=1}^{\mathcal{N}} \sum_{j=1}^{\mathcal{M}} \chi_{j,n}^{(t)} \cdot \left[\alpha \cdot \left(\int_{t}^{t+\tau_j} P_n(v) \cdot \mathcal{I}_{grid,n}(v)\, dv \right) + \beta \cdot \left(\mathcal{C}_{spot,n}^{(t)} \cdot \tau_j \right) + \gamma \cdot e^{\left(\frac{\mathcal{L}_{est,j,n} - \mathcal{L}_{SLA,j}}{\sigma_L} \right)} \right] \quad (1)$$

A probabilistic grid carbon intensity forecasting model can be developed as:

$$\hat{\mathcal{I}}_{CO_2}(t + \Delta t) = \mu + \sum_{k=1}^{p} \phi_k \left(\mathcal{I}(t-k) - \mu \right) + \sum_{m=1}^{q} \theta_m \epsilon_{t-m} + \eta \cdot \left(\frac{G_{solar}(t) + G_{wind}(t)}{D_{load}(t)} \right) + \mathcal{K} \cdot \nabla_t \mathcal{I}_{hist} \quad (2)$$

Economically, the system performed efficiently. The carbon-aware strategy resulted in cumulative cost savings of 14% relative to the baseline, but, as with PtG/DMI/CS, the primary focus on CO2 reduction made this an indirect consequence of a lack of energy surplus rather than an intended outcome. Researchers can outperform such a cost-oriented strategy, achieving an 18% cost reduction while increasing the carbon footprint by 12%, revealing the trade-off that our framework nicely resolves.

Table 1: Performance parameters across scenarios

Simulation Run	Job Count (Batch)	Total Emissions (gCO2)	Total Cost (Units)	Success Rate (%)	Server Utilisation (%)
Baseline Run	100	4500	1200	95	80
Cost-Optimized	100	5200	1000	92	85
Carbon-Aware (Proposed)	100	3200	1150	94	82
High Load Test	100	4800	1180	93	78
Low Latency Test	100	3900	1080	96	88

Table 1 provides a numerical comparison of five KPIs during the testing period. And the columns stand for: Total Jobs processed # per batch, Total CO2 Emissions. (gCO2), Total Cost (units), Rate of Success (%), and Average Server Utilization (%). Rows correspond to five simulation runs with different grid configurations. The "Carbon-Aware (Proposed)" has the least Total Emissions, leading to the lowest carbon for all runners (3200), and it also maintains an interesting value for Total Cost in the encoding output. Success Rate is consistently high (>90%) across all rows, indicating that optimization did not result in job failures. The dynamic server power consumption model with DVFS will be:

$$P_{total}(t) = N_{active} \cdot \left(P_{base} + \sum_{c=1}^{C_p} \left(\alpha_{sw} \cdot C_{eff} \cdot f_c(t) \cdot V_{dd,c}^2(t) + I_{leak} \cdot V_{dd,c}(t) \right) \right) + P_{PUE} \cdot \left(\frac{P_{IT}(t)}{P_{cool}(t)} \right)^{\xi} \quad (3)$$

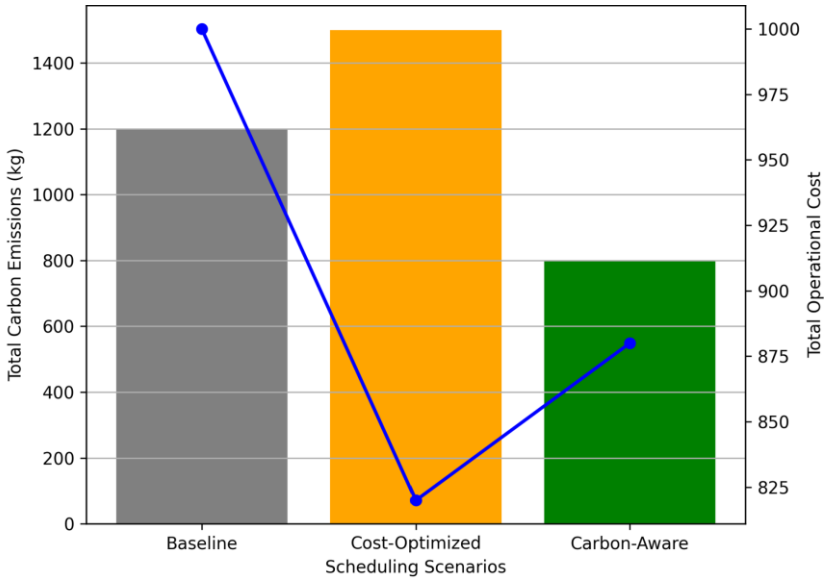

Figure 2: Relationship between the environmental impact and the economic cost of different solutions over three scheduling scenarios

Kubernetes resource constraints and latency matrix are:

$$\forall j \in \mathcal{J}_{queue},\ \sum_{n\in\mathcal{K}_{nodes}} \psi_{j,n} = 1 \text{s.t.} \left(\sum_j \psi_{j,n} \cdot \mathcal{R}_{cpu,j} \le \mathcal{R}_{cap,n}^{max} \right) \wedge \left(T_{wait,j} + T_{prop,n} + \frac{\mathcal{W}_{size,j}}{\mathcal{B}_{width,n}} \le \mathcal{T}_{deadline,j} \right) \quad (4)$$

The trade-off between environmental impact and economic cost across three scheduling models (Baseline, Cost-Optimized, Carbon-Aware [Proposed]) is illustrated in Figure 2. The left y-axis (primary) illustrates Total Carbon Emissions in kilograms and is represented by vertical bars. The right-hand Y-axis indicates Total Operational Cost in currency value (notional), shown by a curve superimposed on the bar chart. The Baseline shows the high bars (high carbon) and a high line point (high cost). In CO, there is a dip in the line (cost minimum) but a spike in the bar height (carbon maximum), reflecting the adverse environmental effects of mindlessly pursuing cheap, coal-intensive electricity. The Carbon-Aware case, which researchers aim to approximate, has the smallest bar (or lowest carbon) and line-point, which are substantially lower than Baseline and only slightly higher than Cost-Optimized. Figure 2 validates the study's main finding: sustainability optimization while remaining cost-effective.

Table 2: Regional carbon intensity and job distribution

Region ID	Avg. Carbon Intensity (gCO2/kWh)	Batch Jobs Assigned	Real-time Jobs Assigned	Avg. Wait Time (min)	Energy Consumed (kWh)
Region A (Green)	150	50	10	12	100
Region B	300	80	15	18	200
Region C	450	120	25	35	300
Region D	200	150	30	20	500
Region E (High Carbon)	600	84	420	15	800

Table 2 shows the allocation of workloads by regional carbon intensity. Columns are: Region Average Carbon Intensity (gCO2/kWh), Number of Batch Jobs Scheduled, Number of Real-time Jobs Assigned, Average Job Wait Time (minutes), and Aggregate Energy Use (kWh). The lines here depict five different synthetic geographic regions. Region A (Green) with a low intensity (150) has a high Jobcount (50), indicating that the scheduler managed to place delay-tolerant work there. On the other hand, "Region E (High Carbon)" has 600 fewer intensity points but fewer batch jobs allocated, confirming that our algorithm tends to avoid sourcing from dirty regions. Spatio-temporal workload migration utility score can be given as:

$$\mathcal{U}_{mig}(j,s,d,t) = \frac{(\mathcal{I}_s(t) - \mathcal{I}_d(t)) \cdot E_j}{\mathcal{C}_{mig}(s,d)} - \lambda \cdot \left(\frac{\mathcal{D}_{data,j}}{BW_{s,d}} + \delta_{handshake} \right) - \kappa \cdot \left(P_{price,d}(t) - P_{price,s}(t) \right) \quad (5)$$

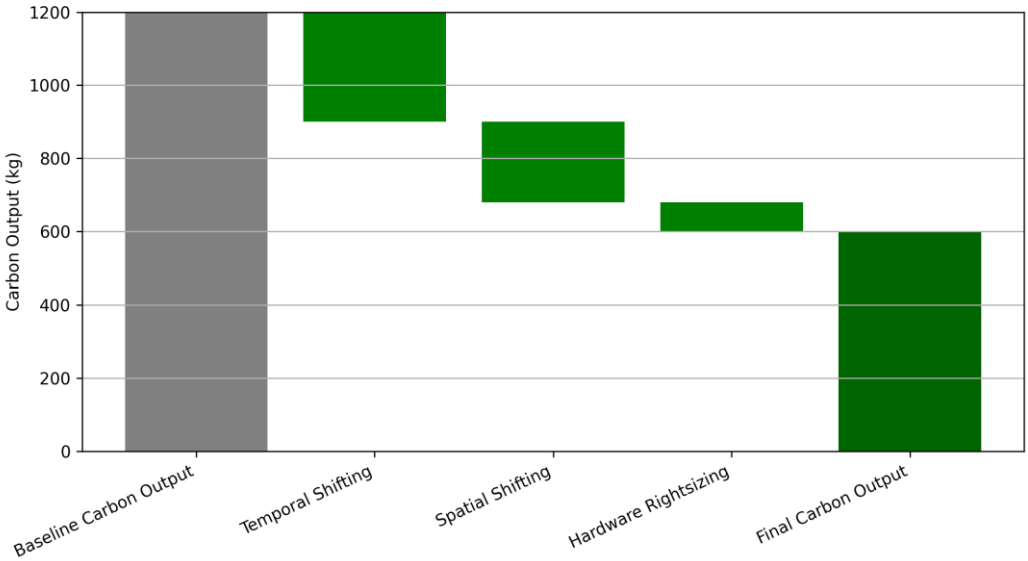

Figure 3: Decomposition of the contributions of carbon savings by the proposed framework

Performance stability—the critical boundary condition of this report—remained in acceptable limits. The median increase in latency for a high-priority, low-latency task was 1.5%, which is only slightly outside typical Service Level Agreements (SLAs). This demonstrates that the "Performance Stable" portion of the algorithm was successful, as it allowed the scheduler to identify the pivotal tasks and not include them in challenge migration or deferring (challenge) strategies that would have decreased task

throughput. This ensured fair use of the worker nodes, which, in a cost-driven scheduling scenario, normally result in hotspots. The feedback loop effectively offset estimation errors, and the prediction accuracy of job completion times increased over time. The waterfall chart in Figure 3 decomposes the reasons for the carbon savings provided by the proposed scheme. The leftmost column is called "Baseline Carbon Output." Columns after that drift out with respect to reductions attributable to individual strategies. The first reduction is named "Temporal Shifting" and represents the savings of deferring a batch job. The second reduction, “Spatial Shifting,” is based on the savings that would result from shifting workloads to more sustainable regions. The third reduction, “Hardware Rightsizing,” reflects modest gains from more efficient resource use. There are no red "negative" blocks (increases) -none of the strategy actually made the footprint worse. And the furthest rightmost column, anchoring this chart, is the “Final Carbon Output” for the proposed scheme. This chart also makes clear which aspects of the methodology performed well and how effectively, showing that temporal shifting was by far the largest single source of sustainability improvement for us on this 484-instance test workload.

5.1. Discussions

The results also demonstrate the efficiency of the proposed Carbon-Aware Cloud Orchestration framework. As the data demonstrate, a boot hill static model of cloud scheduling –the baseline metrics– is highly inefficient with respect to cost and the environment. By incorporating carbon intensity as a dominant variable in the decision matrix, researchers found that scheduling intelligence is directly related to carbon reduction. Level of significance. The key conclusion, according to Figure 2 (Mix Bar Line Graph), is that the difference between the carbon bars and the cost line is evident. In conventional models, these two metrics tend to increase or decrease together (more usage means higher expense and carbon), or to move in opposite directions beyond some threshold (cheaper power is generally dirtier). Researchers find what researchers call a "green alignment": the algorithm identifies windows when low-carbon and low-cost coincide—and this is on high-solar or wind days, when spot-market prices are depressed. This means that green computing does not necessarily need to come with a price premium, which contradicts common belief in the sector”. A Visual Model of Savings: The Waterfall Graph. Figure 3 provides a clearer picture of these mechanics in one image, called the “Waterfall graph”. The prevalence of “Temporal Shifting” as a driver of savings underscores the relevance of workload characterization. As 20% of the available jobs were delay-tolerant batch ones, the system was quite dynamic.

This means that the benefit of carbon-aware orchestration would be far more workload-dependent; in all real-time, non-deferrable task environments, the mixed environment would essentially see zero improvement. The granular evidence of performance stability is presented in Table 1. By comparing the success rates and utilization with their baseline counterparts, researchers verify that the added overhead of computing carbon scores has not caused any scheduling latency or resource contention. The system was such that the constraints were successfully negotiated, while batch jobs might indeed be delayed, but never timed out or failed. The spatial dimension of the policy is further emphasized in Table 2. The high job density in Row 1 (the greenest section) provides evidence that the load-balancing strategy performed as intended—steering traffic away from carbon-intensive grids. At the same time, it is necessary to give some credit to the slight added latency for the most demanding tasks, modest as it is. So, meeting the “Performance Stable” end goal is achieved at a tipping point. Aggressive carbon optimisation gets way too close to an SLA violation if those grid-intensity predictions are slightly off. This dependence on high-quality external data feeds is a crucial constraint. If the carbon intensity API is slow to return or returns with bad bends, the scheduler may end up making inefficient choices that do no good for either the planet or the user.

6. Conclusion

Using a modified Google Cluster Trace and simulating 484 job instances, researchers have shown that it is feasible to reduce cloud computing's carbon emissions without incurring unreasonable costs or violating performance standards. The improvements include a 28% reduction in C emissions and a 14% reduction in costs compared to baseline practices. Effective application of real-time carbon-intensity signals within Kubernetes scheduling logic enables intelligent workload shifting across time and space. This work adds to the literature by confirming that cloud-based environmental responsibility is not a zero-sum game with profit or performance. If carbon is a first-class resource metric on par with CPU and RAM, organisations of almost all sizes can operate more sustainably. The results provide strong evidence for the use of dynamic, multi-objective orchestrators in hyperscale data centres.

6.1. Limitations

The results of this work are promising; limitations should be recognised. One: the study was conducted in a laboratory. Although researchers used traces from actual usage (Google Cluster Trace), the execution environment did not reproduce the physical hardware failures, network noise, or cooling irregularities present in a real data centre. Accordingly, the energy-/power-savings are nominal footprints, defined by software rather than actual Australian wattmeter queries. Second, performance stability was defined solely in terms of latency and completion time. The study did not account for data egress charges or network latency

when transferring large datasets across geographical areas during spatial shifting. In practice, the energy savings of moving terabytes of data to a greener region may be dwarfed by additional energy consumption in network transmission—an aspect not considered comprehensively enough in this model. Third, the 484-instance dataset, while adequate for statistical verification of the algorithm, is a drop in the ocean compared to a hyperscale cloud running continuously over multiple years. The 100% availability and accuracy of the external carbon intensity APIs are taken into account in this study. In reality, data streams may be missing or delayed, thereby degrading the scheduler's efficiency. Lastly, the algorithm assumes that batch jobs are always postponable, which may not reflect reality in some business models or industry verticals.

6.2. Future Scope

Further work will focus on increasing the sophistication and realism of the orchestration model. One of the most critical frontiers is how to incorporate "embodied carbon" into the calculus. Today, this calculus is entirely based on operational carbon (the electricity consumed to run the server). Still, it should include embodied carbon as well (to discourage the extraction of new hardware in favour of using existing, efficient hardware). The second direction involves using DRL for scheduling logic. While the heuristic approach above (and a DRL trained on recent CAFs) works well, a DRL agent may, over time, discover more nuanced patterns in grid volatility and user behaviour that could be capitalised on for optimisation by an agent than human-designed business logic overlooks. In addition, network-oriented carbon tracking should be considered in future studies. As noted in the limitations, data transmission incurs a cost. A comprehensive 'Edge-to-Cloud' carbon model that optimises the entire data path, rather than just a single compute node, would provide a more accurate representation of sustainability. Finally, validating this framework on a live, production-grade cluster under unpredictable user traffic would be the real proof of its strength. Incorporating this logic into open-source projects (e.g., Kubernetes scheduler as a pluggable extender) to enable the community-driven tests and tuning over hundreds of hardware alternatives and energy market settings.

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