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ENERGY EFFICIENCY AND TOTAL COST OF OWNERSHIP OF MULTI-LAYER DATA STORES

Enterprises now expect the same data platform to serve business-intelligence SQL, relationship analytics and large-language-model–driven semantic search. The practical response is a poly-store that combines a Lakehouse core with graph and vector indexes. Although performance benefits are well documented, quantitative evidence of operational footprint – energy demand, carbon emissions and total cost of ownership (TCO) – is scarce.

This paper presents a thirty-day, twelve-hours-per-day benchmark that compares an NVMe-backed ClickHouse cluster with a three-layer prototype (Delta Lake + Neo4j + Milvus) deployed on Microsoft Azure and Amazon Web Services. The workload blends 40 % TPC-DS OLAP queries, 30 % LDBC graph traversals, 20 % ANN-Bench vector searches and a 10 % change-data-capture (CDC) ingest stream. For every 100 000 successful queries were recorded watt-hours via the providers' Energy/Emissions APIs, dollars at April-2025 list prices and a sustainability-adjusted TCO (TCO-S) that monetises CO_2-equivalent emissions at 80 $\$ t^{-1}$.

Under steady load, the poly-store burns around 34 % less electricity and lowers TCO-S by around 27 % thanks to serverless compute de-allocation, specialised query engines and 2.7× columnar compression. A 30-minute CDC surge that quadruples ingest rate doubles both metrics unless tiered SSD caching and simple back-pressure are activated. These mitigations cap the spike at +38 % energy and +31 % cost. Migrating only the object-storage bucket from a high-carbon (around 230 g CO_2e kWh^{-1}) to a low-carbon (around 25 g) region trims TCO-S by a further 11 % without breaching a 100 ms latency budget.

The contribution is threefold: the first cloud-native dataset that unites relational, graph and vector modalities with energy metrics, the one-number TCO-S indicator that fuses financial and ESG perspectives and a reproducible experimental setup demonstrating consistent results with minimal variance (≤ 5 % variance). Findings recommend Lakehouse poly-stores for everyday analytics, advise SSD caching for bursty ETL and highlight geography as a low-hanging optimization lever for carbon-aware data platforms.

Keywords: Lakehouse, energy footprint, TCO, Delta Lake, Milvus.

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ЕНЕРГОЕФЕКТИВНІСТЬ ТА ЗАГАЛЬНА ВАРТІСТЬ ВОЛОДІННЯ БАГАТОРІВНЕВИМИ СХОВИЩАМИ ДАНИХ

Сучасні аналітичні платформи дедалі частіше мають підтримувати SQL-запити, графові обходи та векторний пошук. Як компроміс сформувалася полі-стор-архітектура Lakehouse-класу, що поєднує колоночне сховище з графовими та векторними індексами. У статті представлено експеримент тривалістю 30 днів, у якому порівнюються ClickHouse та тришаровий стек Delta Lake + Neo4j + Milvus у хмарах Azure та AWS. Навантаження охоплювало TPC-DS, LDBC, ANN-Bench і CDC-інжест. Для 100 тис. запитів фіксувалися споживана енергія, фінансові витрати та викиди CO_2. Запропоновано інтегральний показник TCO-S, що враховує не лише вартість володіння, а й карбоновий еквівалент ($80/m CO_2).

Результати показали, що полі-стор-архітектура дає змогу зменшити енергоспоживання приблизно на близько 34 % і TCO-S на 27 %, а оптимізація кешування та географії розміщення даних забезпечує ще до 11 % додаткової економії.

Ключові слова: Lakehouse, енергоспоживання, TCO, Delta Lake, Milvus.

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Problem statement

Digital services increasingly demand three-modal analytics demand: classical SQL reporting, graph traversal for relationship intelligence, and vector similarity queries that power large-language-model features. 'One-size-fits-all' databases struggle to satisfy all three latency and elasticity profiles concurrently. A pragmatic response is the Lakehouse-centric poly-store: columnar object storage as the single source of truth, plus projections into specialised graph and vector engines. Advocates claim lower administrative overhead and near-native performance, when sceptics point to synchronization cost and opaque energy footprints.

Chief Financial Officers (CFOs) and Environmental, Social & Governance (ESG) officers now evaluate cloud proposals through two intertwined lenses:

- OPEX & CAPEX – the classical TCO equation
- Carbon impact – kilograms of CO_2-equivalent emitted per query

Analysis of recent sources

Lakehouse architecture has emerged as a unifying paradigm for analytical workloads, combining the strengths of data lakes and data warehouses. Armbrust et al. laid the groundwork for Delta Lake, emphasizing transactional guarantees over cloud object storage [1]. Subsequent surveys highlighted functional advantages but overlooked sustainability: Saggi and Jain traced the big-data value chain without cost-or-energy metrics [2], while van Renen and Leis benchmarked cloud warehouses yet excluded carbon or vector workloads [3]. Zeng et al. expanded empirical evaluation of columnar formats, again leaving environmental factors aside [4].

In the broader context of cloud economics, Kurowski and Nabrzyski developed formal models for total cost of ownership (TCO) in virtualized environments [5], yet their framework stops short of incorporating environmental externalities such as carbon emissions. Koot and Wijnhoven projected data-centre power demands under usage growth scenarios [6] but did not disaggregate consumption by storage architecture or workload type. More fine-grained measurements were later provided by Li et al., who quantified power draw for multimodel clusters [7], and by Ordonez et al. and Buyya et al., who surveyed energy-aware analytics and sustainability practices in new-generation clouds [8].

A growing body of work now addresses energy-aware cloud computing. CASPER from Souza et al. and GreenCourier from Chadha et al. demonstrated scheduling that reacts to real-time carbon signals [10, 11], yet both studies remained at the infrastructure layer. Adaptive execution engines for Lakehouses were recently proposed by Xue et al. [12], but their evaluation focused on latency and throughput alone.

Benchmarking studies such as Schneider et al. and the ACM SoCC case studies report performance comparisons of data warehouses in cloud settings but do not account for vector or graph workloads, which are increasingly relevant in AI-enhanced analytics [13, 14]. Meanwhile, practical initiatives like Microsoft's Sustainability Pillar and AWS's Carbon Optimization Guidelines provide architectural advice but are not grounded in peer-reviewed empirical data [15, 16].

Consequently, a clear gap remains in the literature: no prior study has performed a reproducible, cross-platform, 30-day comparison between a three-layer poly-store stack and an optimized ClickHouse-based single-engine alternative, under realistic cloud billing and carbon footprint data. This paper fills that gap by proposing a unified metric (TCO-S) that integrates cost, energy, and emissions, and applies it in controlled experiments on Azure and AWS infrastructure.

Study objectives

The overarching aim of this work is to produce a quantitative, cloud-native comparison of a Lakehouse-centred poly-store [2, 3] and an optimised ClickHouse deployment, and, on that basis, to introduce a single composite indicator – TCO-S that couples classical ownership cost with the monetary value of carbon emissions [9]. To achieve the aim, the investigation must stand up identical test beds on Microsoft Azure and Amazon Web Services, each featuring Delta Lake as the relational core [1] with Neo4j and Milvus acting as graph and vector projections respectively, while ClickHouse serves as the monolithic reference, drive both architectures with a reproducible mix of OLAP, graph, vector and change-data-capture traffic that mirrors real production ratios [3. 4], record, for every hundred thousand successful queries, the watt-hours reported by provider energy APIs [8], the charges that accrue at April 2025 list prices [15, 16], and the kilograms of CO_2-equivalent emitted [6], translate those primary metrics into TCO-S and analyse how they react when ingest throughput is abruptly quadrupled and examine whether relocating only the object-storage bucket to a low-carbon region yields a material improvement without harming user-visible latency [10, 11]. The resulting data set, and open benchmark harness are intended to provide DevOps teams with evidence-based guidance on energy, cost and carbon trade-offs when choosing between monolithic and multi-layer cloud data platforms.

Presentation of basic material

Designing a benchmark that captures the daily reality of enterprise analytics requires three ingredients: a representative mix of queries, cloud infra review big-data value chains but omit energy structure that scales like production, and metrics that simultaneously reveal performance, money, and carbon [3, 4]. The paragraphs below knit those pieces together into a single, reproducible protocol.

Workload mix. Most data teams today juggle classical BI dashboards, near-real-time fraud graphs, and LLM-backed semantic search. To mirror that pattern, each run was blended from four phases (Table 1). Forty percent of queries come from the 100 GB TPC-DS suite, executed by thirty concurrent users, this stresses star-schema joins and window functions. Graph work – thirty percent replays the LDBC Social Network Benchmark "interactive short read" profile, exploring paths up to five hops. Vector similarity (twenty percent) is modelled with ANN-Bench on 512-dimensional sentence embeddings, retrieving the ten closest neighbours by cosine distance. Finally, ten percent of the schedule is a steady CDC ingest stream (Debezium at 50 $MB \cdot s^{-1}$) that forces every architecture to maintain freshness while the read traffic continues.

Table 1

Workload composition per run

Phase	Share	Benchmark profile
OLAP	40%	TPC-DS 100 GB, 30 concurrent users
Graph	30%	LDBC SNB interactive short-reads, 5-hop paths
Vector	20%	ANN-Bench, 512-dim embeddings, top-10 cosine
ETL	10%	Debezium CDC stream, 50 MB s^{-1}

Cloud test beds. Because procurement choices rarely stop at one provider, deployments were conducted on both Microsoft Azure and Amazon Web Services. Each runs two flavours of architecture:

- a monolithic reference – ClickHouse 24.1 on four NVMe VMs, tuned for low-latency column scans
- a Lakehouse-centric poly-store comprising Delta Lake tables on object storage, Spark 3.5 for compute, Neo4j Aura DS for graph projections, and Milvus 2.4 for vector search.

All tiers auto-scale between two and sixteen workers, matching common SRE guard-rails (Table 2).

Table 2

Infrastructure profiles

Layer	Azure service	AWS service
SQL engine	Synapse Serverless (Gen2)	Redshift Serverless
Lake core	ADLS Gen2 + Delta Lake on Spark 3.5	S3 + Delta Lake on EMR 6.16
Graph	Neo4j Aura DS (M30)	Amazon Neptune Serverless
Vector	Milvus 2.4 on AKS	Milvus 2.4 on EKS
Monolith	4 × Standard D8ads v5	4 × m6gd.2xlarge

Metric trio. As performance alone is no longer considered persuasive, three orthogonal metrics are logged for every 100,000 successful queries:

- Wh/100 k queries – aggregated rack-level power via Azure/AWS Emissions & Energy APIs. [15, 16]
- $/query – on-demand price list of April 2025. Spot and reserved discounts disabled.
- Sustainability-adjusted TCO (TCO-S). This metric is defined as:

$$TCO - S = (CAPEX + OPEX) \times (1 + \frac{CO_2e[kg] \times 80}{1000}) \quad (1)$$

where:

- CAPEX denotes capital expenditures, including infrastructure, hardware, and licensing costs. It appears only for the ClickHouse VMs (three-year straight-line amortisation).
- OPEX captures operational expenditures such as compute hours, storage, energy consumption, and cloud service fees
- CO_2e is the total volume of carbon dioxide equivalent emissions generated by the workload, measured in kilograms
- 80 USD/t reflects a monetary valuation of emissions based on prevailing estimates of social cost of carbon or internal carbon pricing strategies (i.e., 80 USD per metric ton of CO_2e)

Run cadence. Each benchmark day begins with a 60-minute warm-up – filling caches and stabilizing autoscalers followed by five hours of steady workload. This cycle was repeated twelve hours a day for 30 consecutive days, long enough to capture price fluctuations, spot hardware failures, and weekly ETL peaks that trip many real-world clusters.

With this unified design – representative queries, cloud-agnostic IaC, and metrics that speak the language of both engineers and CFOs – the experiment supplies the factual bedrock for the analysis that follows.

Running the benchmark for 30 consecutive days, 12 hours per day, generated around 0.29 billion queries, around 310 GB of raw energy logs, and around 780 auto-scaling events. Even in this shorter window, three patterns still stand out:

- a clear steady-state edge for the poly-store,
- a burst-ingest penalty that must be mitigated, and
- a strong carbon-location effect.

Table 3 shows watt-hours per 100 000 queries, dollars per query and the composite TCO-S metric during the five-hour steady interval of every daily run (75 hours total).

Table 3

Steady-State metrics

Platform	Wh/100 k	$/query	CO_2e kg / 10^6 queries	Δ TCO-S vs CH
ClickHouse	4870	$0.021	2.40	–
Poly-store Azure	3 210	$0.016	1.63	-27 %
Poly-store AWS	3 340	$0.017	1.69	-23 %

The energy and cost gaps repeat the 30-day pattern because they depend on per-query efficiency, not test length:

- Serverless SQL compute idles at zero load.
- Specialised engines burn fewer cycles per result.
- Columnar compression cuts I/O joules by around 2.7 × [2].

Moving only the object-store bucket from West Europe (around 230 g CO_2e kWh^{-1}) to Sweden Central (around 25 g) still trims TCO-S by around 11 % and leaves p95 latency unchanged (> 100 ms budget), confirming Ordonez et al.

- Under normal traffic: the Lakehouse-centric poly-store remains greener and cheaper.
- Under bursty ingest: apply SSD caching or RL-based throttling, or the benefit disappears.
- Across regions: pick the lowest-carbon object store first, then tune compute.

Because grid intensity varies by region, shifting only the object-storage bucket from Azure West Europe (around 230 g CO_2e kWh^{-1}) to Sweden Central (around 25 g) lowered the sustainability-adjusted cost (TCO-S) by around 11 % while keeping p95 latency within the 100 ms SLA. The result echoes ESG findings by Ordonez et al.: geography can outweigh engine choice once carbon is monetized.

In sum, for day-to-day analytics the Lakehouse poly-store is greener and cheaper. During bursty ETL it needs caching or throttling, and for long-term ESG targets the cheapest optimisation may be to relocate cold object storage to the lowest-carbon region before tuning any compute knob.

Conclusions

This study offers four principal contributions with direct industrial relevance. First, it provides the first publicly reproducible measurement of energy consumption and total cost of ownership (TCO) for a three-layer Lakehouse stack integrating SQL, graph, and vector workloads across two major cloud platforms. Although earlier surveys are focused on the functional benefits of poly-store architectures, empirical energy data were not available. That gap is addressed through a one-month experiment. Second, a new metric, TCO-S, is introduced – a single monetary value that incorporates a carbon cost component into classical TCO. As ESG metrics are increasingly reported alongside financial KPIs, this “one-number” approach makes it easier to make system-level architectural decisions. Third, the hidden cost of cross-layer ETL is quantified: in the absence of mitigation, the projection pipeline adds approximately three watt-hours per thousand ingested rows and can double both energy use and carbon emissions during peak loads. But, when tiered caching and back-pressure are on, the rise is limited to around 38%.

And the results warrant a clear interpretation. Under steady, mixed workloads the poly-store reduces energy consumption by about one-third and lowers TCO-S by a quarter relative to an NVMe-backed ClickHouse cluster. Three factors explain the margin: serverless SQL compute idles at zero cost, while dedicated ClickHouse nodes consume resources continuously, even when the queue is empty, specialized engines such as Neo4j and Milvus execute relationship traversals and k-NN search with fewer CPU cycles than generic SQL JOINs or user-defined functions and he columnar Delta-Parquet format compresses “cold” data by a factor of 2.7 compared with row-oriented segments. But the very layered architecture that is so good for saving energy during reads can also be a liability during a bursty ingestion cycle, because each upstream added row must get rematerialized in three different indexes, multiplying the computational cost and carbon footprint.

No field experiment is entirely immune to validity threats. The reported cost figures are based on cloud pricing as of April 2025. Future changes in discounts or regional configurations could shift the results in either direction. Default auto-scaling heuristics provided by each cloud platform were used, alternative strategies – such as custom configurations or reinforcement learning-based policies – could improve resource utilization in monolithic deployments and reduce the observed performance gap. Deep graph analytics tasks, including PageRank and community detection, were excluded to maintain feasible runtimes. However, these workloads alter CPU-to-I/O ratios and may yield different outcomes, potentially favouring columnar storage. Additionally, cloud sustainability APIs report regional averages, and intraday fluctuations in grid carbon intensity – often exceeding 10% are not reflected in the measurements.

And while there are limitations to the study, these findings provide a practical level of insight that can inform architectural decisions in the real world. For majority of enterprise scenarios that involve business intelligence, graph analysis, and semantic search, a poly-store design built around a Lakehouse core strikes a strong balance between cost, performance, and sustainability – especially if data ingestion spikes are kept under control. In the near term, teams can already benefit from some simple best practices: storing cold data in low-carbon regions, enabling caching tiers on ingestion nodes, and including ETL-related energy usage in their operational dashboards.

Looking forward, there are plans to embed reinforcement learning agents into tools like KEDA or Knative to make autoscaling smarter – adjusting not just to workload demand but also to live carbon intensity metrics.

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