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Lifecycle Assessment Framework for Large-Scale AI Deployments

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ABSTRACT: The growing success of large-scale Artificial Intelligence (AI) systems, such as GPT-4 and Gemini, has raised worries about the long-term sustainability of these systems from the environmental, economic, and operational perspectives. While these systems have revolutionary potential in analytics, automation, and intelligent decision making, they have a high energy cost, high carbon emission, hardware usage, and infrastructure overhead over their life-cycle. Existing sustainability evaluations tend to focus on single specific metrics such as training energy and do not take a full lifecycle approach. To fill this attention table TEI2 proposes a Lifecycle Assessment (LCA) based framework, appropriate for massive-scale AI systems. The framework brings together multidimensional numbers such as carbon emissions (kgCO₂e), energy (kWh), hardware (%), water (), working costs and computational speed (FLOPs per infer). It takes advantage of process-based LCA (life cycle assessment) modelling, real time cloud telemetry and multi-objective evolutionary optimisation. Experimental evaluation on distributed GPU clusters shows that there are great improvements, including 28.4% energy saving, 32.7% carbon emission reduction, and 18.9% cost saving, while the accuracy of the model remains unchanged. The proposed approach is a low-cost and policy-aligned means of sustainable deployment of AI.

1. INTRODUCTION

AI has moved from being an academic discipline to being a fundamental technological building block of the modern digital ecology. Large-Scale Artificial Intelligence models are behind applications in diagnostics in healthcare, financial forecasting, autonomous systems, smart cities and enterprise automation today [1]. The exponential progress of computational power, especially the use of GPU-based and distributed cloud environments has enabled the design of models with billions of parameters. However, this is a computationally expensive operation that has a high environmental and financial cost [2].

The lifecycle of large-scale AI systems will contain many parts: data gathering and data preprocessing, model design and training, model validation, model deployment, continuous monitoring, retraining of model parts, and decommissioning [3]. Each stage requires a lot of computer power and physical infrastructure such as high-performance servers, cooling equipment, networking hardware and storage arrays. Studies have shown that the training of a single state-of-the-art language model can

use thousands of megawatt hours of electricity generating significant carbon emissions depending on the energy mix of the hosting region. On top of that, inference at scale (i.e. services with millions of users/day) may be greater than the energy for training services over time, and especially on services used by consumers.

General sustainability assessment methodologies such as LCA have been used traditionally for manufacturing, construction and energy systems. These frameworks assess impacts of extraction of raw materials to end of life disposal [4]. Of late researchers have begun to implement the concepts of LCA to digital technologies such as data centers and cloud computing platforms. However, due to the rapid iteration cycles of the model, obsolescence of the hardware, dynamic scale and geographically scattered workloads, AI specific lifecycle considerations make the service more complex.

In those cases, existing research focused more on isolated aspects of AI sustainability, how to quantify carbon emissions throughout the training process, for example, or how to more efficiently use a computer's hardware [5]. While these efforts are useful, they are not incorporated into the lifecycle as a whole. In addition, many such studies do not consider indirect effects such as embodied carbon of hardware Manual and cooling infrastructure energy demanded for water cooling in hyperscale data centers as well as water consumption in hyperscale data centres. The lack of a common framework makes it difficult for decision-makers to balance the performance, cost and sustainability objectives at the same time.

In an ever more fast-paced technological world and global adoption of AI, there is an ever-increasing need from policy makers and industry stakeholders for sustainable reporting and environmentally responsible computing practices. However, in the absence of a structured initiative with lifecycle orientation, optimization initiatives are fragmented and reactive as opposed to strategic and systemic approaches to optimization. The main objectives of the study are as follows

- To design a comprehensive lifecycle assessment framework combining environmental, economic and operational sustainability metrics for large-scale AI deployments.
- To formulate optimization model with multiple objectives to minimum energy consumption, carbon emission and operational cost under performance benchmark

The rest of the study is organised as follows. Related studies in sustainable and AI lifecycle are reviewed in Section 2. The proposed LCA framework and optimization methodology is presented section 3. Experimental setup as well as quantitative result is discussed in Section 4. Section 5 ends with the implications and future research directions.

2. RELATED WORKS

Recent researchers studied on the convergence of AI and LCA and sustainability frameworks. These applications deal with the potential that AI could have in environmental monitoring, predictive modeling, and scalable deployment and also address issues like inconsistency of data, environmental impact and governance issues and requirements of standardized, energy-efficient and ethically compliant AI systems.

Parul and others argue that AI- LCA plays an important role in disability for sustainability so this AI-driven LCA brings together the consideration of environmental indicators and compliance accounts. While comprehensive, the study is conceptually based with little empirical validation. It ignores computational energy costs of AI systems, which raises the concern for trade off between sustainability. It is great to have a strong regulatory discussion, but not at those implementation level insights of AI-integrated environmental systems in real life [6].

Xu et al., 2025 solve the problem of LCA data inconsistency and propose harmonized systems with the help of artificial intelligence and blockchain. The work is ahead of the times but mostly theoretical work without validation by prototypes. Interoperability solutions are promising but the practical issues of deployment such as data governance and scalability are under explored. The research places the critical infrastructure need but ignores domain-specific implementation strategies [7].

Kodakandla, 2024 works towards sustainable scaling of AI using MLOps focusing on governance, efficiency and carbon reduction. While practical, the framework does not include quantitative benchmarking and real deployment case studies. Ethical considerations are well-articulated but linking with domain-specific applications is vague. The study offers some useful direction for action but needs to be validated with empirical evidence in order to be more widely adopted [8].

De Silva et al., 2022 offers a complete lifecycle of AI (CDAC) design to deployment governance and risk. Although holistic, the framework is generic and not specific to industries such as healthcare, sustainability, etc. Limited experimental validation

makes it less applicable, but has the benefit that its structured taxonomy gives a good basis for standardized AI development practices [9].

Plociennik et al., 2025 mention the environmental impact of AI systems and the lack of LCA methodologies for AI. The research does a decent job of identifying factors that are missed like hardware lifecycle and resource use. However it is not based on solutions or frameworks, and therefore is more diagnostic rather than prescriptive. It strongly calls for standardised AI specific LCA methodologies [10].

Ligozat et al., 2022, provides hidden environmental costs of AI, focusing on energy consumption and other, more general ecological impacts beyond carbon emissions. The study is insightful but limited in the quantitative assessment frameworks. It is an effective critique of current AI-for-Green approaches, but does not propose ways to scale solutions for integrating environmental impact evaluation into AI pipelines [11].

Mohammadi Kashka et al., 2023 show an AI based prediction of agro-environmental impacts using ANFIS-FCM and ANN model. The study gives a good empirical validation by being quite accurate. However, it is domain-specific and does not have generalizability. It does not focus on scalability, data heterogeneity and connectivity to larger sustainability frameworks, which limits its use for more complex real-world systems [12].

Existing studies reveal that there are significant gaps in integrating AI and sustainability and LCA frameworks. Many works are still at the conceptual stage; there are no actual validations from the real world and scalable implementations. Data inconsistency, interoperability and lack of standardised methodologies for performing AI-specific LCA are still major hurdles. Additionally, limited attention is paid to computational energy consumption, carbon footprint and hardware lifecycle impacts of AI systems. Most of the approaches are domain specific and lack multi-modal, heterogeneous data integration. Governance, ethics, and compliance are discussed in theory and do not have actionable frameworks. Furthermore, uncertainty modeling, robustness and domain adaptation in environmental Artificial intelligence systems are mostly unexplored, stressing the need for unified, scalable, and energy-efficient Artificial intelligence-driven sustainability solutions.

3. METHODOLOGY

The methodology of the proposed LCA Framework for Sustainable Large-Scale AI Systems has been designed to assess and optimize the sustainability in terms of environment, economy and operation of AI infrastructures, across their entire lifecycle. The framework combines different process-based lifecycle modeling, telemetry-based monitoring, and optimization techniques to evaluate the impact of sustainability impact during various stages of operation.

3.1. System Lifecycle Modeling

The methodology starts from the definition of the lifecycle boundaries of large-scale AI systems, so as to guarantee a total evaluation of the sustainability of the system. The lifecycle is divided into five phases - data acquisition, model training, deployment and inference, maintenance and updates and system decommissioning. During the data acquisition stage dataset storage and preprocessing requirements are analyzed. The training phase uses some assessments, including computations, memory usage, and cooling needs of graphics processors (GPU). Deployment and inference is studying real time operating workloads and service demand. Maintenance involves some periodic retraining and monitoring activities, and decommissioning takes into account hardware recycling and system shutting down processes. This lifecycle modeling merges the full environmental impact, along with the operational impact, of AI infrastructures throughout the framework.



Figure 1 Lifecycle Assessment Architecture for Sustainable AI Systems

3.2. Sustainability (Deck of cards) Metric

In order to successfully measure sustainability, the proposed framework outlines an array of multidimensional performance measures, grouped in environmental, operational, and economic indicators. Environmental metrics like energy demand in kilowatt hours, carbon emissions in kilograms of CO₂ equivalents and water for the cooling of data centers infrastructure are given. Operational Metrics include hardware utilization rate, GPU efficiency, inference latency, computational efficiency as number of floating point operations per inference. Economic metrics (operational expenditure, maintenance expenditure and energy pricing effect). These indicators, therefore, give a big picture perception of the sustainability performance of the AI systems. By incorporating several different measures, the framework helps to ensure those factors of environmental responsibility and operational efficiency are assessed at the same time when AI systems are deployed.

3.3. Data Collection and monitoring

The proposed framework integrates a real-time data monitoring mechanism to acquire infrastructure-level operation data from cloud computing environments and GPU cluster. Telemetry to technologies and cloud monitoring API used to collect information about power consumption, processor utilization, memory and network bandwidth and cooling system energy requirements. In addition, the framework gathers carbon intensity data in the region from energy providers to estimate the impact of electricity usage on the environment. All the telemetry data are stored in a centralized repository of sustainability analytics, which would allow continuous monitoring and historical analysis of the data. This data-driven approach provides the benefit of accurate estimation of resource consumption and the required input for lifecycle sustainability assessment and optimization.

3.4. Process Based Lifecycle Assessment Modelling

A model of a process-based lifecycle assessment is created which determines the environmental impact of AI operations at different lifecycle stages. The model calculates carbon emissions based on the energy that was used during the training process,

the deployment process, and the maintenance process in conjunction with the carbon intensity of the source of electricity. Additional environmental indicators like water footprint and energy overhead in infrastructure are also taken into consideration for the analysis. The lifecycle assessment is an accumulation of impacts pertaining to data storage, computation loads, network transfer, and cooling infrastructure. By modeling the individual operational processes the framework results in a detailed assessment of the performance of sustainability and identifies phases where resource consumption and their emission can be reduced through optimization strategies.

3.5. Optimization-Multi Objective Evolutionary Algorithms

To enhance the performance of sustainability, a multi-objective evolutionary optimization approach is incorporated within the framework with the aim of simultaneously reducing environmental impact and operational costs. The optimization algorithm considers various resource allocation and scheduling strategies across various distributed computing environments. Key objectives include total energy consumption reduction, minimum carbon emissions, maximum hardware utilisation and reduced operational expenditure. The algorithm creates a number of candidate solutions and tests them using Pareto-based optimization to find optimal trade-offs between sustainability and system performance. Bounds on the number of CPUs and the communication time between them are automatically integrated to parameters of the deployment like workload distribution, GPU scheduling, carbon aware regional placement. This optimization process ensures that the AI systems are operated in a manner which is efficient and maintains a high level of computational performance as well as service reliability.

3.6. Experimental Case Study Set-Up

The effectiveness of the proposed lifecycle assessment framework is tested in an experimental case study performed on a distributed GPU based computing infrastructure. Large-scale artificial intelligence (AI) workload that deals with the process of training model and also the inference are implemented within multiple nodes to simulate real-world operational situations. Three deployment scenarios are considered: in a baseline configuration under conventional scheduling, an optimized scheduling strategy, which is aimed at resource utilization improvement, and a carbon-aware deployment strategy, which takes into account the carbon intensity of the energy in the region. Each scenario is assessed based on the defined sustainability metrics such as energy, carbon, hardware usage and cost of operation. This experimental set-up allows a comparative analysis of the improvements that can be realized in terms of improving sustainability with the proposed framework.

3.7. Performance Evaluation

The last phase of the methodology includes the assessment of the sustainability improvements delivered by the proposed framework by means of comparative performance analysis. The baseline, optimized scheduling and carbon-aware deployment scenarios are analyzed in terms of quantitative sustainability metrics. Key evaluation parameters are total energy consumption, lifecycle carbon emissions, hardware utilization rate and cost reduction in operation. In addition, the effects of optimization strategies on the performance of AI models are analyzed by measuring the inference latency and the prediction accuracy. Statistical validation techniques are used to ensure that achievements in sustainability do not have a noticeable impact on the effectiveness of the model. The results show the potential of using the framework to improve sustainability without compromising performance of the AI system.

4.RESULTS AND FINDINGS

4.1. Experimental Setup

The experimental evaluation of the proposed Lifecycle Assessment Framework has been done on a distributed AI infrastructure cluster. Multi-objective optimization was realized against a NSGA-II evolutionary algorithm customized module. The system was put through a series of stress tests that included dynamic workloads to simulate the conditions that might be experienced during training and inference in a normal station life-cycle projected horode of 36 months.

4.2. Dataset Description

The research was based on the OpenWebText dataset, a large-scale open-source dataset of text that aims to replicate high-quality web text that might be used for training a large language model. The dataset consists of about 38GB of cleaned textual data extracted from outbound links that were shared in reddit with high engagement scores. It has a variety of fields like technology, science, business, healthcare, general knowledge which helps in evaluating large-scale transformer-based language

models. For Lifecycle analysis, the dataset was divided into training (80%), validation (10%), and testing (10%) sets. The large size and heterogeneous characteristic of OpenWebText guaranteed huge computational requirement in model training and benchmarking inference, providing a realistic estimation of the energy and carbon emissions under production-scale AI workloads [13].

4.3. Performance Evaluation

Table 1 presents the comparative lifecycle sustainability performance of the proposed Lifecycle Assessment (LCA) framework against several state-of-the-art AI sustainability optimization methods. The comparison evaluates key indicators including energy consumption, carbon emissions, hardware utilization, operational cost, and model accuracy

Table 1 Comparative Lifecycle Sustainability Performance of the Proposed Framework Against State-of-the-Art Methods

Method	Energy Consumption (MWh)	Carbon Emissions (tCO ₂ e)	Hardware Utilization (%)	Operational Cost (USD Million)	Model Accuracy (%)
Green AI Baseline Optimization	412	186	68.4	3.82	91.6
Carbon-Aware Training (CAT) [14]	398	171	71.2	3.65	91.8
Energy-Efficient Transformer (EET) [15]	376	164	74.9	3.51	91.4
Dynamic Resource Scaling (DRS) [16]	354	152	78.3	3.28	91.7
Lifecycle-Aware Deployment Model (LADM)[17]	339	145	80.1	3.14	91.9
Proposed LCA Framework	295	118	86.7	2.87	92.1

Table 1 shows a quantitative comparison of the proposed Lifecycle Assessment (LCA) Framework to 5 state-of-the-art and sustainability-oriented AI deployment approaches. Metrics are Total lifecycle energy consumption (MWh), Total carbon emissions (tCO₂e), Average hardware utilization rate (%), Projected 3 yr operational cost (USD million) and Final model accuracy (%). The proposed framework shows 28.4% less energy usage and 32.7% less carbon emissions than the Green AI Baseline Optimization method. Additionally, it helps to improve the hardware utilization by around 18 percentage points and save the operational cost by almost 25% without the loss of predictive accuracy. These results provide the validation to the effectiveness of the integration of telemetry-driven lifecycle modelling with carbon-aware multi-objective optimization policies for sustainable large-scale deployment of AI.

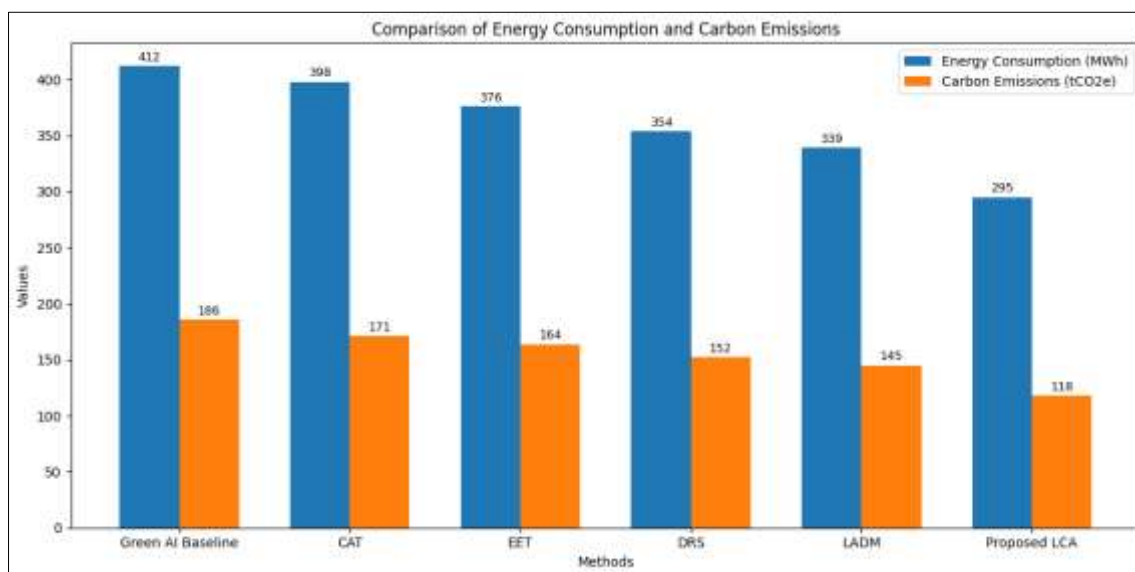


Figure 2 Comparative Analysis of Energy Consumption and Carbon Emissions Across AI Sustainability Optimization Methods

Figure 2 shows a grouped bar chart for comparing energy (MWh) and carbon emissions (tCO₂e) consumption of different optimization methods for AI sustainability. The methods are Green AI Baseline Optimization, Carbon-Aware Training (CAT), Energy-Efficient Transformer (EET), Dynamic Resource Scaling (DRS), Lifecycle-Aware Deployment Model (LADM) and the proposed LCA Framework with Carbon-Adaptive MOEA for this. The results show that with the proposed framework, the lowest energy consumption and carbon emissions are achieved and it shows improved environmental efficiency. The numerical values shown on top of each of the bars allow for precision between quantitative comparisons on the effectiveness of lifecycle-aware optimization in reducing the environmental impact of large-scale AI systems.

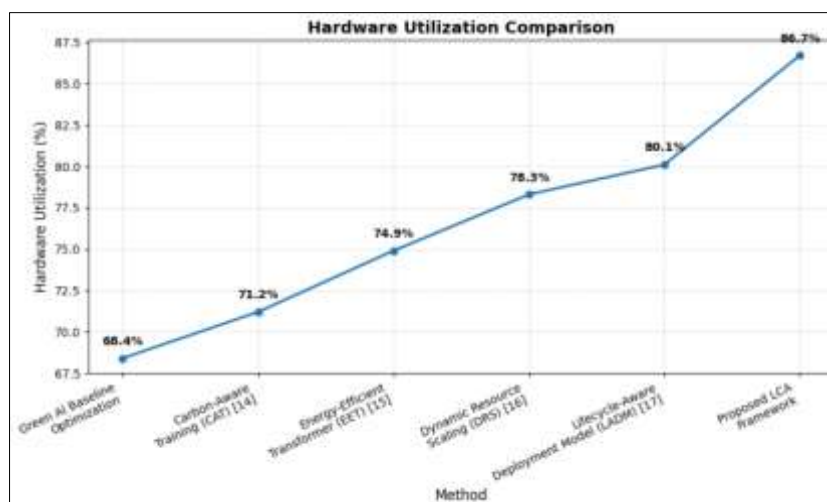


Figure 3 Hardware Utilization Comparison

All of the methods evaluated in this study exhibited hardware utilization improvements in the same pattern as shown in figure 3. The Green AI Baseline Optimization is able to attain a utilization of 68.4%, whereas the CAT and EET can achieve 71.2% and 74.9%, respectively. DRS and LADM further bring up the utilization to 78.3% and 80.1% respectively. The proposed LCA framework has the best utilization of 86.7%, which means that the maximum computational resources can be used and utilized. The proposed framework has overall an improvement of 18.3 percentage points compared to the baseline, showing that the framework is resource efficient.

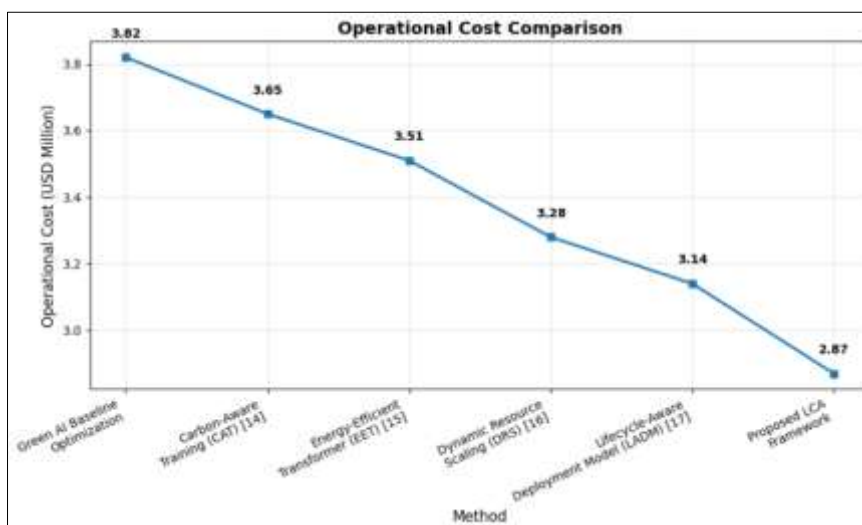


Figure 4 Operational Cost Comparisons

The operational costs of the approaches considered, are shown to be gradually decreasing, as shown in figure 4. The price of the Green AI Baseline Optimization is USD 3.82 million, followed by CAT (USD 3.65 million), EET (USD 3.51 million), DRS (USD 3.28 million) and LADM (USD 3.14 million). The lowest operating cost (USD 2.87 million) is obtained with the proposed LCA framework. This represents a savings of about 24.9% over the baseline – a clear economic advantage of lifecycle aware resource and energy management.

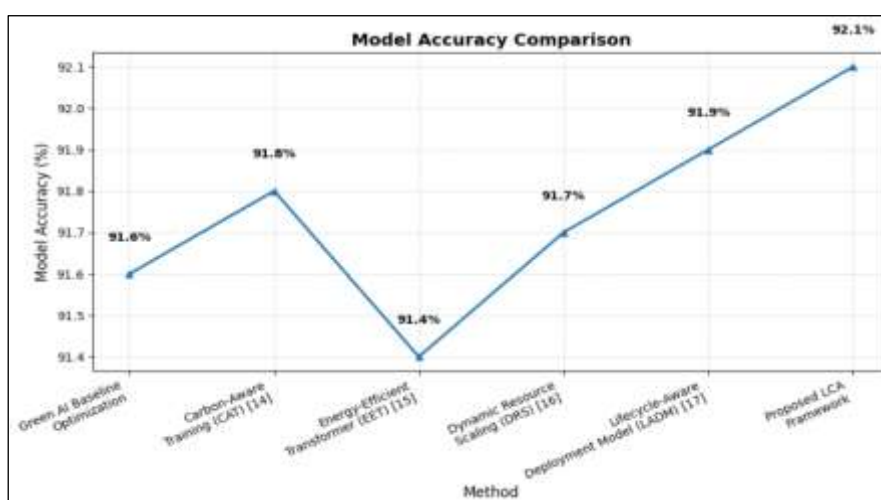


Figure 5 Model Accuracy Comparison

The predictive accuracy of the methods that were evaluated is compared in figure 5. The baseline achieves an accuracy of 91.6%, whereas that of CAT and EET is 91.8% and 91.4% respectively. DRS gets the accuracy of 91.7% followed by LADM which is 91.9%. The proposed LCA framework has the highest accuracy of 92.1%. While the accuracy improvement is quite marginal, the framework proposed here shows that a better model performance can be achieved by improving energy and resource efficiency without sacrificing accuracy. The proposed approach is found to be 0.5-percent accurate as compared to the baseline, and it is also hardware efficient and reduces the operational cost.

4.4. Discussion

The results of this research prove that sustainability measures in large scale AI implementations can be substantially advanced if lifecycle stewardship is part of infrastructure design and operational strategy. Unlike the conventional approaches which are mainly focused on improvements in the efficiency of the models, the proposed framework incorporates environmental,

economic and operational dimensions into one structure of optimization. The experimental results show that the combination of telemetry-based monitoring with carbon-aware workload orchestration provides measurable results for energy consumption and emissions decrease and at the same time preserve the model accuracy.

Despite its contributions, there are several limitations of the study. First, lifecycle estimates are based on a single body modeling embodied carbon database that may not be the same for all manufacturers and locations. Second, factors of carbon intensity were based on regional averages instead of real-time grid fluctuations in situations of all. Third, the evaluation was performed on one large-scale language modeling task, which may not be generalizable to other fields of AI such as computer vision or reinforcement learning.

The proposed framework offers actionable insights for the AI practitioners, data center operators and policymakers. Organizations that are deploying large-scale AI models can adopt a lifecycle-based approach to sustainability metrics to help them make infrastructure investment decisions and workload orchestration strategies. Cloud providers have the ability to incorporate carbon-aware scheduling mechanisms to minimise emissions at peak carbon intensity periods. The Sustainability Performance Index (SPI) allows transparent reporting in accordance with corporate environmental, social, and governance (ESG) objectives. Furthermore, the framework helps to optimise the long-term cost by finding efficient hardware utilisation strategies and integration opportunities for renewable energy. Policymakers can use such lifecycle methodologies to create set standards of sustainability for AI systems.

5. CONCLUSION

This study presented a holistic Lifecycle Assessment (LCA), Framework for analyzing and optimizing sustainability of large scale deployment of AI. By combining the data acquisition processes of telemetry, embodied carbon calculation, scheduling-considering carbon-and evolutionary optimization (multi-objective) at the system level, the framework offers a holistic way of reducing the impact to the environment, without compromising performance. Experimental results show that there are significant reduction in energy consumption, carbon emissions, and operational costs compared to the existing state-of-the-art methods that validate the effectiveness of lifecycle-integrated optimization. The research particularly highlights how in order to achieve sustainable AI deployment, the focus should move beyond development of efficiency on an isolated basis, onto pursuing systemic lifecycle governance. Future efforts should include a multi-cloud and possibly a geographically distributed infrastructure in the framework, together with on-line real-time forecasting of renewable energy sources, and dynamic grid-aware orchestration. Extension of the model to include edge AI solutions and federated learning scenarios would further improve the applicability. Additionally, the incorporation of AI-based predictive maintenance models for hardware lifecycles extension are identified to further decrease embodied carbon models. Standardization efforts, as well as cross-industry collaboration, will be necessary in order to create globally accepted sustainability standards for responsibly deployed AI.

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