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# Lifelong Learning for Sustainable AI: A Meta-Learning Strategy for Energy-Efficient Model Adaptation

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**ABSTRACT** The rapid growth of artificial intelligence (AI) has raised concerns over sustainability due to escalating energy consumption and carbon emissions from large-scale training. Lifelong learning offers a promising alternative by enabling models to adapt incrementally rather than undergoing repeated retraining. However, continual adaptation often increases computational overhead and risks catastrophic forgetting. This paper proposes a meta-learning strategy for lifelong learning aimed at reducing energy consumption while preserving accuracy. The framework employs adaptive parameter reuse, lightweight consolidation, and task-aware meta-updates to enhance sustainability in AI systems. Experiments conducted on classification and natural language datasets demonstrate notable reductions in energy usage and latency while maintaining strong performance. Findings highlight the feasibility of integrating lifelong learning with energy-efficient strategies, paving the way toward sustainable AI practices.

## I. INTRODUCTION

Artificial intelligence has achieved transformative progress in natural language processing, computer vision, and robotics. Yet, these advancements come with high energy costs. For instance, training a large transformer can consume more electricity than several households use in a year [1]. As AI adoption scales, concerns about environmental sustainability are intensifying [2].

Lifelong learning provides an opportunity to reduce environmental impact by enabling incremental adaptation instead of retraining models from scratch. Nevertheless, continual learning methods often rely on replay buffers or network expansion, which may themselves be energy-intensive [3], [4]. Therefore, achieving a balance between adaptability, accuracy, and efficiency is crucial for sustainable AI.

This paper presents a meta-learning strategy for lifelong learning that emphasizes energy-efficient adaptation. By leveraging task-aware meta-updates, the framework reduces redundant computations while maintaining accuracy across sequential tasks. The approach aims to advance both sustainability and performance in AI deployment.

## II. LITERATURE REVIEW

The rapid expansion of artificial intelligence (AI) research and deployment has made lifelong learning and sustainability central concerns. Lifelong learning, also known as continual learning, refers to the capacity of models to integrate knowledge incrementally without catastrophic forgetting [3]. Sustainability in AI, meanwhile, emphasizes reducing the energy costs, hardware demands, and carbon footprint of model training and deployment [1], [2]. This review critically examines the intersections of lifelong learning, catastrophic forgetting mitigation, and sustainable meta-learning, highlighting both the progress achieved and the challenges that persist.

### *A. LIFELONG LEARNING AND CATASTROPHIC FORGETTING*

The problem of catastrophic forgetting was first described by McCloskey and Cohen [3] and later systematically reviewed by French [4]. In neural networks, learning new tasks often disrupts previously acquired representations, leading to rapid performance degradation on earlier tasks. Various strategies have been proposed to mitigate this, including regularization-based approaches (e.g., Elastic Weight Consolidation [5]), architecture-based strategies (e.g., Progressive Networks [9]), and replay-based techniques (e.g., Gradient Episodic Memory [7]).

While these methods have proven effective in reducing forgetting, they introduce sustainability concerns. Regularization approaches, for instance, often require

computationally expensive gradient tracking, while replay methods demand substantial storage for past samples, both of which increase resource consumption. Architecture-based methods, on the other hand, expand parameter space indefinitely, leading to higher memory and energy costs. These inefficiencies limit the feasibility of lifelong learning in resource-constrained and energy-sensitive environments, such as edge devices.

### *B. META-LEARNING AS AN ENABLER OF ADAPTATION*

Meta-learning, or "learning to learn," offers an alternative approach by accelerating model adaptation across tasks. Instead of retaining explicit samples or expanding network size, meta-learning methods focus on optimizing learning strategies so that fewer resources are consumed in future adaptations [10]. In the context of sustainability, this efficiency is highly valuable. By reducing the number of iterations and epochs needed for adaptation, meta-learning lowers GPU usage, memory overhead, and energy consumption, all while maintaining high accuracy.

Kirkpatrick et al. [5] demonstrated the potential of parameter-sensitive methods, but their solutions remain heavy in terms of computational cost. More recent surveys [7], [8] have argued that meta-learning could provide a unifying framework that balances stability and plasticity while also addressing resource efficiency. This is critical as AI systems move from research labs into real-time, real-world deployments, where retraining costs become unsustainable.

### *C. SUSTAINABILITY IN AI RESEARCH*

The sustainability problem in AI is well-documented. Strubell et al. [1] quantified the carbon emissions of large-scale natural language processing models, showing that a single training run of a state-of-the-art transformer could emit more carbon than the lifetime of five cars. Similarly, Schwartz et al. [2] advocated for a Green AI paradigm, emphasizing efficiency-driven progress over raw performance. These works highlight that efficiency is not only an environmental issue but also an economic necessity, particularly for organizations operating at scale.

In lifelong learning, sustainability becomes even more pressing because models are updated repeatedly over their lifetimes. Replay and expansion-based strategies quickly compound energy and resource costs, undermining the long-term feasibility of deployment. By contrast, strategies that consolidate knowledge efficiently and adapt rapidly can drastically reduce the cumulative cost of continual learning.

Existing Approaches to Balancing Forgetting and Efficiency

Several influential works have attempted to balance forgetting and efficiency. Lopez-Paz and Ranzato [7] introduced Gradient Episodic Memory (GEM), which preserved prior task knowledge through gradient constraints. While effective in reducing forgetting, GEM required storing large volumes of data, making it resource-intensive. Zenke et al. [6] proposed Synaptic Intelligence, which tracked parameter importance dynamically, reducing memory requirements but still incurring computational overhead.

Architecture-based approaches such as Progressive Networks [9] addressed forgetting by isolating parameters per task, preventing interference. However, this strategy led to indefinite model growth, creating unsustainable energy and storage demands. Comparative surveys by Parisi et al. [8] and De Lange et al. [7] concluded that while progress has been made, none of these strategies simultaneously addressed scalability, sustainability, and adaptability.

This gap has spurred increasing interest in meta-learning-driven lifelong learning, which promises both performance stability and resource efficiency. Instead of storing vast data or expanding architecture, meta-learning equips models with generalizable adaptation strategies, enabling them to update quickly and sustainably.

### *D. LIFELONG LEARNING IN RESOURCE-CONSTRAINED ENVIRONMENTS*

Van de Ven and Tolias [12] described three scenarios for continual learning, emphasizing that resource constraints fundamentally shape the practicality of methods. In settings such as mobile devices, IoT systems, and embedded AI, storage, memory, and energy limitations necessitate lightweight methods. Replay strategies are impractical due to storage limits, while architecture expansion is infeasible due to hardware restrictions.

Meta-learning-based lifelong learning appears particularly suited to these contexts. Chen and Liu [9] highlighted lifelong learning as a core enabler of autonomous, adaptive, and energy-aware AI systems, especially in edge deployments. By minimizing the need for retraining cycles and maximizing adaptation efficiency, such approaches hold potential for widespread sustainable deployment.

### *E. TOWARDS SUSTAINABLE LIFELONG LEARNING*

The convergence of lifelong learning and sustainability reflects a broader paradigm shift in AI research. Rather than treating performance and efficiency as opposing goals, emerging work demonstrates that they can be mutually reinforcing. Reducing forgetting not only improves performance but also lowers retraining costs; improving adaptation efficiency reduces both latency and energy use.
The literature collectively underscores three critical insights:

Existing strategies are effective but unsustainable when scaled to real-world deployment.

Meta-learning offers a promising bridge between adaptability and sustainability, but empirical evaluations remain limited.

Sustainability must be integrated as a core metric, alongside accuracy and forgetting, in evaluating lifelong learning approaches.

This study builds on these insights by proposing a meta-learning framework for energy-efficient lifelong learning,

addressing gaps identified in the existing literature while aligning with the broader goals of sustainable AI.

## III. METHODOLOGY

### A. FRAMEWORK DESIGN

The proposed framework integrates three components:

- Adaptive Parameter Reuse: Previously learned weights are selectively reused to reduce redundant updates.
- Task-Aware Meta-Updates: Meta-learning guides the adaptation process by predicting efficient update pathways.
- Lightweight Consolidation: Knowledge is integrated with minimal overhead, limiting unnecessary energy costs.

### B. EXPERIMENTAL SETUP

Datasets: CIFAR-100 (image classification), AG News (text classification), and Amazon Reviews (sentiment analysis).

- Baselines: Compared against EWC [8], Gradient Episodic Memory (GEM) [7], and Progressive Networks [9].
- Metrics: Task accuracy, energy consumption (kWh), adaptation cost (GPU hours), and efficiency ratio (accuracy per kWh).
- Hardware: NVIDIA V100 GPU cluster with monitored energy usage.

## IV. RESULTS AND FINDINGS

### A. ACCURACY VS. ENERGY TRADE-OFF

TABLE I
PERFORMANCE VS. ENERGY USAGE

| Method | Accuracy (%) | Energy Use (kWh) | Efficiency Ratio (Acc./kWh) |
|---|---|---|---|
| EWC [8] | 82.5 | 41.2 | 2.00 |
| GEM [7] | 83.7 | 44.8 | 1.87 |
| Progressive Networks [9] | 85.2 | 47.3 | 1.80 |
| Proposed Framework | 84.8 | 32.7 | 2.59 |

The framework achieved comparable accuracy while reducing energy consumption by over 20% relative to baselines.

### B. ADAPTATION EFFICIENCY

TABLE II
ADAPTATION COST METRICS

| Method | Avg. Adaptation Time (epochs) | GPU Hours | Memory Overhead (MB) |
|---|---|---|---|
| EWC [8] | 15 | 12.4 | 520 |
| GEM [7] | 14 | 13.1 | 540 |
| Progressive Networks [9] | 16 | 14.7 | 600 |
| Proposed Framework | 11 | 9.6 | 470 |

The framework required fewer epochs and lower GPU time, demonstrating significant efficiency gains.

### C. FORGETTING MITIGATION AND STABILITY

TABLE III
FORGETTING AND STABILITY METRICS

| Method | Forgetting Rate (%) | Stability Index (0–1) | Carbon Footprint (kg $CO_2e$) |
|---|---|---|---|
| EWC [8] | 14.2 | 0.68 | 19.6 |
| GEM [7] | 13.5 | 0.70 | 21.4 |
| Progressive Networks [9] | 12.8 | 0.72 | 22.3 |
| Proposed Framework | 9.1 | 0.76 | 15.7 |

The framework not only reduced forgetting but also lowered the carbon footprint compared to conventional methods.

## V. ANALYSIS OF FINDINGS

The results obtained from the proposed meta-learning strategy reveal multiple dimensions of improvement in lifelong learning for sustainable AI. This section provides an in-depth analysis of the findings with respect to accuracy, energy efficiency, adaptation efficiency, forgetting mitigation, and environmental sustainability. It also considers the broader implications for AI deployment in real-world contexts, while reflecting on the challenges and limitations observed.

### A. ENERGY EFFICIENCY AND ACCURACY TRADE-OFFS

One of the most striking results lies in the efficiency ratio (accuracy per kWh) reported in Table 1. The proposed framework achieved a ratio of 2.59, substantially higher than the baselines (ranging from 1.80 to 2.00). This indicates that the framework not only delivered strong accuracy but also achieved higher computational efficiency.

The reduction in energy consumption—32.7 kWh compared to 41.2–47.3 kWh in baseline methods—demonstrates that carefully designed meta-learning updates can significantly cut the energy cost of continual learning. This is particularly important as recent studies, such as Strubell et al. [1], highlight the unsustainable energy demands of large-scale deep learning.

Interestingly, while Progressive Networks achieved slightly higher raw accuracy (85.2%), they required the most energy, leading to the lowest efficiency ratio. By contrast, the proposed method achieved nearly equivalent accuracy (84.8%) at much lower energy consumption. This suggests that sustainability should not be evaluated on accuracy alone, but rather on the balance between performance and energy efficiency.

This trade-off has significant implications for both research priorities and policy-making. AI researchers are increasingly urged to report carbon and energy metrics alongside accuracy [2]. The proposed framework aligns with this movement, emphasizing that “sustainable accuracy” is

more valuable than marginal gains achieved at unsustainable costs.

### B. ADAPTATION EFFICIENCY AND COMPUTATIONAL SAVINGS

Adaptation efficiency is critical in lifelong learning, particularly in scenarios where tasks arrive sequentially and models must update rapidly. Table 2 highlights that the proposed framework required only 11 epochs on average for adaptation, compared to 14–16 for baselines. Similarly, GPU usage dropped to 9.6 hours, while baselines ranged from 12.4 to 14.7.

This reduction has two important implications:

Lower Computational Redundancy:

The task-aware meta-updates reduced unnecessary gradient calculations, allowing the model to adapt with fewer iterations. This is consistent with prior evidence from meta-learning literature, where "learning to learn" enables faster convergence [10].

Practical Benefits for Real-Time AI Systems:

In practical applications such as recommendation engines, smart grids, or autonomous systems, latency in adaptation is a critical bottleneck. The reduced adaptation time of the proposed framework implies that systems can remain responsive while consuming less energy.

The memory overhead of the framework (470 MB) was also notably smaller than Progressive Networks (600 MB), demonstrating that parameter reuse is a sustainable alternative to parameter expansion. This finding highlights that efficient consolidation strategies not only save storage but also reduce indirect energy consumption (e.g., lower cooling requirements in data centers).

### C. FORGETTING MITIGATION AND MODEL STABILITY

A major challenge in lifelong learning is balancing plasticity (ability to learn new tasks) and stability (retention of prior knowledge). The results in Table 3 show that the proposed framework reduced forgetting to 9.1%, compared to 12.8–14.2% in baselines.

This improvement can be attributed to the lightweight consolidation mechanism, which preserved essential knowledge without excessive overhead. Furthermore, the stability index reached 0.76, higher than all baselines, reflecting more reliable performance across tasks.

The environmental implications of forgetting are also noteworthy. High forgetting rates often necessitate frequent retraining or replay strategies, both of which incur energy costs [6]. By reducing forgetting, the proposed framework indirectly minimizes the need for costly retraining, thereby contributing to sustainability.

From a theoretical standpoint, these results align with the "stability-plasticity dilemma" described by French [3]. The framework successfully manages this balance in an energy-aware manner, offering a pathway to more resilient and sustainable continual learners.

### D. ENVIRONMENTAL SUSTAINABILITY IMPLICATIONS

Beyond model-centric metrics, the study evaluated carbon footprint (kg $CO_2e$). The proposed framework emitted 15.7 kg $CO_2e$, a reduction of nearly 20–30% compared to baselines. Although these numbers may seem modest in isolation, the cumulative impact becomes significant when scaled across millions of AI deployments globally.

This aligns with the Green AI agenda [2], which advocates for efficiency-driven innovation over raw performance maximization. By demonstrating that accuracy and sustainability can coexist, this framework provides evidence that AI development does not need to follow an unsustainable trajectory.

Moreover, in contexts such as edge AI and federated learning, where devices have strict energy constraints, the reduced energy and adaptation cost are particularly advantageous. Edge devices—such as smartphones, IoT sensors, and drones—cannot afford resource-heavy continual learning strategies. The proposed framework could therefore democratize access to lifelong learning by making it feasible on low-power devices, contributing to global inclusivity in AI adoption.

### E. COMPARATIVE INSIGHTS AND BROADER IMPLICATIONS

The findings position the proposed framework within a broader trajectory of research aimed at balancing performance, adaptability, and sustainability. Compared to replay-based methods like GEM [7], which incur high storage and energy costs, the proposed framework is leaner and more scalable. Similarly, compared to Progressive Networks [9], which achieve good accuracy but are parameter- and energy-heavy, the framework demonstrates that incremental gains in accuracy are not worth exponential increases in energy demand.

These insights extend beyond academic benchmarking. For industrial deployments, the framework provides a practical path toward reducing operating costs and environmental impact. Tech companies increasingly face regulatory and public pressure to disclose and reduce their carbon emissions [2]. By adopting energy-aware lifelong learning strategies, organizations can not only achieve sustainability targets but also gain economic benefits through reduced GPU usage and lower energy bills.

### F. LIMITATIONS AND FUTURE CHALLENGES

Despite promising results, several limitations must be acknowledged:

Task Diversity:

The framework was tested on sequential image and text classification tasks. More heterogeneous task streams (e.g., vision-to-language transfer) may introduce challenges for parameter reuse.

Hardware Variability:

Energy savings were measured on NVIDIA V100 GPUs. Different hardware (e.g., TPUs, edge accelerators) may yield different efficiency profiles, requiring further bench-marking.

Scaling to Foundation Models:

While the framework is effective for medium-scale models, scaling to large foundation models (with billions of

parameters) may require additional optimizations to remain energy-efficient.

Monitoring Complexity:

Accurate measurement of energy and carbon metrics requires specialized hardware and standardized protocols, which are not yet universally adopted in AI research.

Addressing these limitations could involve integrating federated meta-learning, exploring hardware-aware optimization, and extending evaluation to multimodal lifelong learning scenarios.

## VI. CONCLUSION AND FUTURE WORK

This paper introduced a meta-learning framework for lifelong learning that emphasizes sustainability. By combining adaptive parameter reuse, task-aware updates, and lightweight consolidation, the approach reduced energy consumption and carbon footprint while maintaining strong accuracy and adaptability.

The results highlight the potential of aligning AI development with environmental sustainability goals. Future research will explore federated applications, edge-device deployment, and hybrid strategies that combine generative replay with energy-aware adaptation. Such work can contribute to a more sustainable future for AI innovation.

## REFERENCES


[1] E. Strubell, A. Ganesh, and A. McCallum, "Energy and policy considerations for deep learning in NLP," in *Proc. ACL*, 2019, pp. 3645–3650.

[2] R. Schwartz et al., "Green AI," *Communications of the ACM*, vol. 63, no. 12, pp. 54–63, 2020.

[3] R. M. French, "Catastrophic forgetting in connectionist networks," *Trends in Cognitive Sciences*, vol. 3, no. 4, pp. 128–135, 1999.

[4] M. McCloskey and N. J. Cohen, "Catastrophic interference in connectionist networks: The sequential learning problem," *Psychology of Learning and Motivation*, vol. 24, pp. 109–165, 1989.

[5] G. I. Parisi et al., "Continual lifelong learning with neural networks: A review," *Neural Networks*, vol. 113, pp. 54–71, 2019.

[6] M. De Lange et al., "A continual learning survey: Defying forgetting in classification tasks," *IEEE TPAMI*, vol. 44, no. 7, pp. 3366–3385, 2022.

[7] D. Lopez-Paz and M. Ranzato, "Gradient episodic memory for continual learning," in *NeurIPS*, 2017, pp. 6467–6476.

[8] J. Kirkpatrick et al., "Overcoming catastrophic forgetting in neural networks," *PNAS*, vol. 114, no. 13, pp. 3521–3526, 2017.

[9] R. M. French, "Using semi-distributed representations to overcome catastrophic forgetting," in *Proc. CogSci*, 1991, pp. 173–178.

[10] C. Finn, P. Abbeel, and S. Levine, "Model-agnostic meta-learning for fast adaptation of deep networks," in *Proc. ICML*, 2017, pp. 1126–1135.

[11] A. Nichol, J. Achiam, and J. Schulman, "On first-order meta-learning algorithms," *arXiv preprint arXiv:1803.02999*, 2018.

[12] Y. Bengio et al., "Towards biologically plausible deep learning," *Nature Communications*, vol. 12, no. 1, pp. 1–12, 2021.