ESTIDAMAA
Vol. (2026), 2026, pp. 55-67
ISSN: 3078-428X

Research Article

Generative AI Data Centers and the Net-Zero Challenge: A Multi-Dimensional Assessment of Energy Demand and Carbon Emissions

Tirus Muya[1, *], Kassem Hamze[2],

[1] Department of computer science, Murang'a University of Technology, Kenya

[2] Faculty of Engineering-Islamic University of Lebanon, Lebanon

ARTICLEINFO

Article History

Received 1 Apr 2026

Revised: 15 May 2026

Accepted 13 Jun 2026

Published 01 Jul 2026

Keywords

Generative Artificial Intelligence,

Data Centers, Sustainability,

Carbon Emissions,

Net-Zero,

Renewable Energy,

Power Usage Effectiveness,

Python Simulation.

ABSTRACT

As Generative Artificial Intelligence (AI) is booming, demands for large-scale data center infrastructure are skyrocketing and electricity usage, carbon emissions and global Net-Zero goals are a growing concern. This study introduces a lightweight Python-based simulation framework to evaluate the long-term environmental sustainability of Generative AI data centers across four key development pathways: Baseline, High Growth, Efficiency, and Green Transition. The proposed framework combines publicly available energy and environmental data sets to provide an estimate of annual electricity demand, carbon emissions, renewable energy contribution, Power Usage Effectiveness (PUE), cumulative emissions, and the Net-Zero Gap Index (NZGI) from 2025 to 2050. Results from simulations show that significant differences in environmental performance exist between the scenarios investigated. The least sustainable development pathway is the High Growth scenario which has the highest demand for electricity (3000 TWh), carbon emissions (540 $MtCO_2e$), and cumulative carbon emissions (13,234.70 $MtCO_2e$) by 2050. The Green Transition scenario both reduces electricity demand (1350 TWh) via optimising operational performance in the system, and provides an energy mix with the lowest annual carbon emissions (64 $MtCO_2e$) and highest level of renewable energy (90%) to meet future climate targets, with the smallest Net-Zero Gap Index (1.88), showing greatest alignment with future climate targets. The results show the potential benefits of optimizing the use of energy in data center operations, and how quickly renewable energy can be deployed to maximize potential environmental impacts of Generative AI infrastructure. The proposed framework is transparent, computationally efficient and reproducible, and can offer decision support tools for researchers, policymakers and industry stakeholders to follow sustainable AI development paths towards Net-Zero.

1. INTRODUCTION

Today, Generative Artificial Intelligence (GenAI) has revolutionized computing, enabling the creation of advanced applications in areas such as natural language processing, computer vision, scientific research, and intelligent automation. Large Language Models (LLMs) or any other foundation models have contributed in a major way to the demand for computational resources, which has led to an unprecedented speed of hyperscale data centres around the world [1]. One of the largest consumers of electricity is these facilities, which need a large amount of electricity to train and run AI models and cool down the data centers [2].

As AI infrastructure continues its expansion, new issues of energy sustainability and climate change mitigation have arisen. On the other hand, some countries are accelerating their shift towards renewable energy, but the growing demand for electricity by AI data centers may outpace the renewable energy supply, increasing the reliance on fossil fuel power generation and greenhouse gas emissions [3]. This has raised concerns about the coherence of the rapid development of the AI infrastructure with global commitment to the Net-Zero targets of international climate policies [4].

More recent research has been conducted on the relationship between the role of AI in electricity demand, power system planning, and carbon emissions. Previous research has revealed that the adoption of AI can greatly contribute to high electricity demand, resulting in increased electricity generation requirements and stress on the electricity transmission and infrastructure systems [5]. Moreover, increased proportion of renewable energy in power generation and better data center efficiency (such as lower Power Usage Effectiveness [PUE] values) have been recognized as key approaches to reduce environmental impacts [6].

*Corresponding author email: Tmuya@mut.ac.ke
DOI: https://doi.org/10.70470/ESTIDAMAA/2026/004

These contributions are significant, but most of the existing contributions have been limited to case studies of regions, especially in Europe, and they have been very complex optimisation methods that necessitate the use of extensive data sets and computing power [7-10]. This approach might restrict repeatability and wider application of AI infrastructure planning in global situations. Thus, a streamlined and adaptable assessment mechanism that can assess the global impacts of the environmental side effects of expanding AI data centers is still needed. To address this, the effect of Generative AI data centers on electricity demand, carbon emissions and Net-Zero goals is measured in this research paper using an easy-to-follow multi-dimensional framework. The proposed framework is developed based on the scenario simulation in python using publicly accessible energy and environmental dataset. Four scenarios are considered to explore how the energy use and carbon emissions will change in the future (2025–2050) in the presence of AI growth, energy efficiency gains, and renewable energy penetration. The key findings of this research are given as follows:

1. Development of a simplified global framework for assessing the environmental impact of Generative AI data centers.
2. Implementation of a Python-based scenario simulation model using publicly available datasets.
3. Evaluation of the relationships among electricity demand, carbon emissions, renewable energy integration, and PUE.
4. Introduction of a Net-Zero Gap Index (NZGI) to quantify deviations from carbon neutrality targets under different AI growth scenarios.

2. RELATED WORK

In the last few years, the rapidly evolving Generative Artificial Intelligence (GenAI) has gotten more and more research focus because of its effects on global electricity demand, carbon emissions, and sustainability. The recent research has primarily aimed at quantifying the environmental impacts of AI data centers, predicting future energy consumption, and examining how to incorporate renewable energy sources into AI systems. The key studies on AI data centers, energy consumption, and the Net-Zero targets are summarized in Table I.

TABLE I. SUMMARY OF RECENT STUDIES ON AI DATA CENTERS AND SUSTAINABILITY

Ref.	Methodology	Main Findings	Limitation
[11]	IMF-ENV Computable General Equilibrium Model	Investigated the impact of AI-driven data center growth on electricity demand, electricity prices, and carbon emissions under different policy scenarios.	Focused primarily on macroeconomic impacts with limited infrastructure-level sustainability analysis.
[12]	Mixed Integer Linear Programming (MILP)	Evaluated AI-driven electricity demand, generation capacity, and Net-Zero pathways across multiple European scenarios.	Limited to the European power system and requires complex optimization models.
[13]	Workshop Report	Discussed electricity use, emissions, and policy implications of AI-related data centers.	Provides policy recommendations without quantitative simulation.
[14]	Technical Review	Reviewed AI energy demand, greenhouse gas emissions, and long-term sustainability opportunities.	Does not develop a simulation framework for comparative scenario analysis.
[15]	Sustainability Review	Examined AI data center impacts on power system sustainability, renewable integration, and operational flexibility.	Mainly reviews existing approaches without proposing a simplified predictive model.

The last few years have seen numerous studies that show the electricity consumption and carbon emissions from AI-driven data centers are becoming a significant contributor to global electricity demand and carbon emissions. The majority of studies are based on advanced optimization or economic modelling for future energy needs and decarbonization pathways, but some also offer broad reviews of the sustainability issues and policy implications. Many approaches that are currently available, however, either treat the regional power systems or use highly detailed data sets and computational intense optimization methods.

Hence, a simplified global assessment framework is proposed in this study based on publicly available datasets and scenario-based simulation that evaluates the relationships between electricity demand, carbon emissions, renewable energy integration and performance of Net-Zero by implementing it in Python. The proposed approach is meant to provide a computational efficient, reproducible solution that can be used for sustainability assessment and strategic decision-making.

While various studies have contributed to the growing knowledge about AI's energy usage and carbon footprint, they employ distinct approaches and focus on varying aspects of AI usage. Table II provides a comparison of the main methodological aspects between representative existing works and the proposed work, while emphasizing the key differences.

TABLE II. COMPARISON BETWEEN EXISTING STUDIES AND THE PROPOSED FRAMEWORK

Feature	Existing Studies	Proposed Study
Assessment Scope	Primarily regional (e.g., Europe)	Global assessment
Methodology	Optimization-based (e.g., MILP) or technical reviews	Python-based scenario simulation
Computational Complexity	High	Moderate
Data Sources	Regional or infrastructure-specific datasets	Publicly available global datasets

Sustainability Indicators	Energy demand and carbon emissions	Energy demand, carbon emissions, renewable energy, PUE, and NZGI
Reproducibility	Limited due to complex optimization models	High through a lightweight simulation framework
Scenario Analysis	Region-specific scenarios	Four global AI development scenarios
Net-Zero Assessment	Included in some studies	Integrated with the proposed Net-Zero Gap Index (NZGI)

Table II shows that the proposed framework differs from the current works that focus on specific assessment models that are heavy weight, domain specific, and not reproducible, as well as being implemented in Python and being globally applicable. The framework also incorporates several sustainability metrics and includes the Net-Zero Gap Index (NZGI) which aims to provide a more holistic assessment of the environmental impacts of AI.

3. RESEARCH GAP AND CONTRIBUTIONS

There has been a rise in usage of Generative Artificial Intelligence with concerns regarding its sustainability in the long run. Some recent research efforts have been published to better understand the effect that these AI data centres have on electricity usage, carbon emissions and energy system planning [16] but most of the research has been related to high-level optimization and special cases. Therefore, a need exists for a more efficient, reproducible and broadly deployable assessment approach.

A need in the current literature is a universal approach to determine the correlation between the electricity demand, CO2 emissions and the integration of renewable energy with efficiency indicators such as Power Usage Effectiveness (PUE). Most of the studies are focused on one of these factors individually or on very specific optimizations models, which hinders comparative evaluations of sustainability by researchers and decision makers.

To fill this gap, in this study, a simplified global scenario-based simulation framework is introduced which is programmed in the Python language. The proposed methodology is more comprehensive than the standard optimization-based methodologies, as it accounts for publicly available energy and environmental data along with a lightweight simulation model, to evaluate different sustainability metrics across different future scenarios of AI growth. This approach is used to ensure analytical transparency, less computational complexity and is reproducible. This research has accomplished the following:

1. A simplified global framework for assessing the environmental sustainability of Generative AI data centers.
2. A Python-based scenario simulation using publicly available datasets.
3. An integrated assessment of electricity demand, carbon emissions, renewable energy penetration, and PUE within a single analytical framework.
4. A Net-Zero Gap Index (NZGI) to evaluate deviations from carbon neutrality pathways under different AI growth scenarios.

4. METHODOLOGY

This research presents a simplified scenario-based method for assessing the environmental impact of Generative AI data centers in terms of global electricity usage, carbon emissions and Net-Zero targets. The proposed framework, based on public data and a light simulation (done in Python), allows for the evaluation of several sustainability indicators in different scenarios of the development of artificial intelligence, compared with optimization-oriented strategies that require a complex model of the infrastructure. The proposed scheme is subdivided into five steps as illustrated in Fig. 1.

4.1 Stage 1: Data Acquisition

The first step in this process is to collect the publicly-available data for AI data center usage, electricity generation, percentage of renewables used, carbon intensity, and Power Usage Effectiveness (PUE). The datasets are sourced from international organisations and industrial sustainability reports, ensuring consistency and reliability.

4.2 Stage 2: Data Preprocessing

Standardization of collected datasets is done with data cleaning, normalization and handling of missing values. Data from annual electricity used, renewable energy percentage, carbon emission factors, and the growth rate of AI infrastructure is retrieved and fed into the model.

4.3 Stage 3: Scenario Development

Four hypothetical scenarios were created to represent various possible routes of development to assess potential environmental impacts of Generative AI infrastructure. The Basic scenario assumes status quo in technology and policy, and is a projection of the current deployment of AI. High-Growth Scenario is one in which AI services are increasing in growth and in which hyperscale data centers consume more electricity. The Efficiency Scenario is based on the idea that the energy efficiency of data centers will be continually improved over time through reductions in Power Usage Effectiveness (PUE) from hardware and cooling technology advances. Lastly, the Green Transition Scenario reflects a moderate growth of AI with higher shares of renewable energy, which equates to a sustainable growth trajectory that aligns AI development with sustainability goals. These scenarios can provide a strong basis for examining how different models of AI development can affect energy consumption, carbon emissions, and the path to a more sustainable future, all while contributing to a more sustainable and resilient future.

4.4 Stage 4: Python-Based Simulation

A scenario-based simulation model was built in Python to model the environmental impact of the data centers behind Generative AI from 2025 to 2050. The simulation combines publicly available data sets and the proposed assessment framework to calculate future electricity demand, carbon emissions, renewable energy usage and operating efficiency for the four development scenarios. The model calculates the annual electricity usage for each simulation year based on annual growth in the number of AI servers, estimates annual carbon dioxide (CO_2) emissions from AI infrastructure based on the electricity carbon intensity (ECI) and analyzes the impact of AI electricity generation infrastructure's penetration and the improvement of Power Usage Effectiveness (PUE). The results of the simulations are then compared to determine the environmental trade-offs of various pathways of AI development. Main computational tasks involved in the simulation process are summarized in Table III.

TABLE III. PYTHON SIMULATION WORKFLOW

Step	Simulation Task	Output
1	Load publicly available energy and environmental datasets	Input variables
2	Preprocess and normalize the collected data	Clean simulation dataset
3	Initialize one of the four development scenarios	Scenario parameters
4	Estimate annual electricity demand (2025–2050)	Energy demand (TWh)
5	Calculate annual CO_2 emissions using carbon intensity factors	Carbon emissions ($MtCO_2$)
6	Estimate renewable energy contribution	Renewable energy share (%)
7	Evaluate operational efficiency using PUE	Energy efficiency indicators
8	Compute the Net-Zero Gap Index (NZGI)	Sustainability assessment
9	Compare simulation outputs across all scenarios	Comparative performance analysis

The generated simulation results provide the basis for evaluating the sustainability of AI data centers and identifying the impact of different AI growth trajectories on future energy demand and carbon neutrality objectives.

4.5 Mathematical Formulation

The proposed simulation framework is an approach that uses a set of simplified mathematical formulations to estimate the electricity demand and associated environmental impacts of Generative AI data centers in the future. These formulations form the computational backbone of the Python-based simulation and are used to calculate electricity demand, carbon emissions, renewable energy contribution, cumulative emissions and progress towards Net-Zero targets for various development scenarios.

$$E_t = E_{yi}\left(\frac{E_{yi+1}}{E_{yi}}\right)^{\frac{t-yi}{yi+1-yi}} \quad (1)$$

- E_t is the estimated annual electricity demand in year t.
- E_{yi} is the electricity demand at the beginning of the interpolation interval.
- E_{yi+1} is the electricity demand at the end of the interpolation interval.
- y_i denote two consecutive anchor years.

This formulation enables piecewise interpolation between successive anchor years (2025, 2030, 2035, and 2050), allowing the simulation to represent different growth rates during each development stage.

$$C_t = E_t \times CI_t \quad (2)$$

where

- C_t denotes annual CO_2 emissions;
- CI_t represents the electricity carbon intensity.

$$R_t = \frac{RE_t}{E_t} * 100\% \quad (3)$$

where

- R_t is the renewable energy contribution
- RE_t is renewable electricity generation

$$CC = \sum_{t=2025}^{2050} C_t \quad (4)$$

CC denotes cumulative carbon emissions during the simulation period.

$$NZGI_t = \frac{C_t - C_t^{Target}}{C_t^{Target}} \quad (5)$$

where

- C_t^{Target} is the target emission level required to achieve Net-Zero.

Positive NZGI values reflect emissions higher than the desired Net-Zero pathway, while negative values reflect environmental performance that is superior to the desired pathway. All of the above mathematical equations provide the basis for calculations using the proposed simulation framework in Python. In every simulation cycle, the equations are sequentially applied to simulate the annual electricity consumption, carbon emissions, contribution of renewable technologies, cumulative emissions and the Net-Zero Gap Index for each development scenario. The computed outputs are then assessed with the sustainability performance indicators listed below. Algorithm 1 summarizes the key computational steps that are performed by the simulation model, which is implemented as a Python program, to enhance the repeatability of the proposed framework. The algorithm shows the sequential process of data acquisition, data pre-processing, scenario evaluation and sustainability assessment.

Algorithm 1. Proposed Python Simulation Procedure

Step	Description
Input	Public energy datasets, AI growth scenarios, simulation parameters
Step 1	Load and preprocess the collected datasets
Step 2	Initialize scenario-specific parameters
Step 3	Estimate annual electricity demand
Step 4	Compute annual carbon emissions
Step 5	Estimate renewable energy contribution
Step 6	Evaluate PUE
Step 7	Compute NZGI
Step 8	Compare simulation outputs across all scenarios
Output	Sustainability indicators, comparative tables, as well as graphical visualizations

The algorithm is the computational workflow of the proposed framework and guarantees that all the development scenarios are assessed following a well-defined sequence of computations. The outputs that are generated are then assessed using the sustainability performance measures below.

4.6 Stage 5: Sustainability Assessment

The last part of the proposed framework is assessing the environmental sustainability of Generative AI data centers based on simulation results for each of the development scenarios. Several key sustainability measures are discussed such as annual electricity usage, carbon emissions, share of renewables, Power Usage Effectiveness (PUE) and the proposed Net-Zero Gap Index (NZGI). These metrics collectively provide a holistic assessment of the environmental efficiency and sustainability of AI systems, including energy consumption, efficiency, carbon footprint, and carbon neutrality. All of this is then compared to the effects of various AI growth trajectories on future energy consumption, GHG emissions and overall progress towards the Net-Zero goals. The results of this assessment help to inform policymakers, energy planners and developers of AI infrastructure on how to ensure that technological development doesn't compromise environmental sustainability over time. The overall workflow of the proposed assessment framework is shown in Figure 1: The data used in the proposed assessment framework is publicly available data on energy and environmental aspects, which are then preprocessed, scenarios generated, simulated using Python, evaluated for sustainability, and compared with the results.

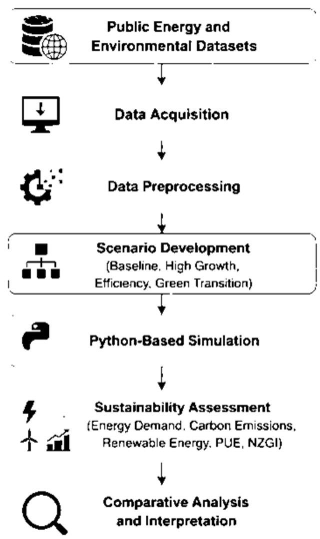

Fig. 1. Proposed Assessment Framework

5. EXPERIMENTAL SETUP

To determine the environmental footprint of Generative AI data centers in various development scenarios, the experimental evaluation was carried out with the assistance of a simulation framework built in Python. The suggested framework combines publicly accessible energy and environmental data with scenario-based forecasting methods to forecast future electricity demand, carbon emissions and contribution from renewables, and operational efficiency, between 2025 and 2050. This simulation was designed to develop a repeatable and efficient computational model to assess energy consumption by AI and to enable comparative sustainability analysis of the different pathways to AI growth. The experimental setup used in this work is summarized as follows: Experimental setup is summarized in Table IV.

TABLE IV. EXPERIMENTAL CONFIGURATION

Parameter	Configuration
Simulation Platform	Python 3.x
Programming Libraries	NumPy, Pandas, Matplotlib, SciPy
Data Sources	Publicly available energy and environmental datasets
Study Period	2025–2050
Assessment Scope	Global AI Data Centers
Number of Scenarios	4
Performance Indicators	Electricity Demand, Carbon Emissions, Renewable Energy Share, PUE, NZGI
Output Format	Tables, Comparative Analysis, and Graphical Visualization

After collecting and pre-processing the data, the simulation was run independently for each development scenario. Electricity demand for each year was projected based on the projected AI growth rate and carbon emissions were estimated based on the corresponding AI electricity carbon intensity. Measures of renewable energy penetration and of Power Usage Effectiveness (PUE) have been added to assess their impact on sustainability performance. Lastly, the simulation results were analyzed for differences in environmental impact and towards achieving Net-Zero targets across different scenarios.

5.1 Data Sources

For the proposed framework to be implemented, various public datasets from well-known organizations were used as input parameters for simulations. These datasets can be used to determine the quantitative value information necessary for estimating electricity demand, calculating carbon emissions, assessing renewable sources and analyzing operational efficiency. Table V outlines the main datasets and model simulation variables used to calibrate the Python-based model. The sources we chose include internationally renowned estimates of data centre electricity demand, grid carbon intensity, renewable electricity generation, growth in data centre demand due to AI, and operational efficiency of data centers.

TABLE V. PRIMARY DATA SOURCES USED IN THE SIMULATION

Data Category	Simulation Variable	Unit
Data Center Electricity Consumption	Annual Global Data Center Electricity Demand	TWh/year
Electricity Carbon Intensity	Global Average Grid Carbon Intensity	gCO_2e/kWh
Renewable Electricity	Renewable Share of Global Electricity Generation	%
AI Data Center Growth	Scenario-Specific Annual Demand Growth Rate	%/year
Power Usage Effectiveness	Average Data Center PUE	Dimensionless

These data sources were used to apply to the proposed Python-based model. The variables were assigned values on the basis of the simulation parameters so that all the experimental scenarios were consistent.

5.2 Simulation Scenarios

Four scenarios were introduced in Section 4.3, and were each implemented independently in the experimental evaluation. All scenarios were simulated with the same conditions and by changing only the three parameters, AI growth rate, renewable energy penetration, and operational efficiency. This setup allows for comparing sustainability indicators for multiple pathways of AI development in a comparable way. Table VI shown the simulation scenarios.

TABLE VI. SIMULATION SCENARIOS

Scenario	Description	Expected Impact
Baseline	Assumes the continuation of current AI infrastructure growth and existing energy policies without significant technological changes.	Moderate increase in electricity demand and carbon emissions.
High Growth	Represents accelerated deployment of Generative AI services and rapid expansion of hyperscale data centers.	Highest electricity demand and CO_2 emissions due to increased computational workloads.
Efficiency	Assumes continuous improvements in data center energy efficiency through reduced PUE and advanced cooling technologies.	Lower electricity consumption and reduced carbon emissions compared with the Baseline scenario.
Green Transition	Combines moderate AI growth with higher renewable energy penetration and cleaner electricity generation.	Improved sustainability performance and enhanced progress toward Net-Zero objectives.

The proposed scenarios were independently simulated using the Python-based framework, providing the ability to compare the scenarios and assess their impact on electricity consumption, carbon emissions, renewable energy utilization, and overall environmental sustainability.

5.3 Simulation Parameters

Parameters summarised in Table VII were used to set up the proposed simulation. These parameters represent the control conditions for all the experimental cases, and are set before the Python simulation is run.

TABLE VII. SIMULATION PARAMETERS

Parameter	Unit	Description	Source
Electricity Demand	TWh/year	Annual electricity consumed by AI data centers	IEA / Public Energy Statistics
AI Growth Rate	%/year	Annual increase in AI computational demand and infrastructure expansion	Recent AI market reports
Renewable Energy Share	%	Percentage of electricity supplied from renewable energy sources	IRENA / IEA
Carbon Intensity	kg CO_2/kWh	Carbon emissions associated with electricity generation	Ember / IEA
Power Usage Effectiveness (PUE)	–	Indicator of data center operational energy efficiency	Industry sustainability reports
Simulation Period	Years	Time horizon used for scenario evaluation	2025–2050

Once the parameters are set, the Python simulation uses the same parameters throughout the various experimental cases. Different development paths for AI are evaluated in this section with consistent and comparable environment performance through scenario-specific modifications such as variations in AI growth rate, renewable energy penetration, or PUE.

5.4 Performance Metrics

The simulation outputs generated from each experimental scenario were evaluated using the performance metrics summarized in Table VIII.

TABLE VIII. PERFORMANCE METRICS

Metric	Unit	Description
Annual Electricity Demand	TWh	Total annual electricity consumed by AI data centers.
Annual Carbon Emissions	$MtCO_2$	Annual CO_2 emissions resulting from electricity consumption.
Cumulative Carbon Emissions	$MtCO_2$	Total accumulated CO_2 emissions over the simulation period (2025–2050).
Renewable Energy Contribution	%	Percentage of electricity supplied from renewable energy sources.
Power Usage Effectiveness (PUE)	–	Indicator of the operational energy efficiency of AI data centers.
Net-Zero Gap Index (NZGI)	–	Measures the deviation between estimated carbon emissions and the targeted Net-Zero pathway.

The results of the simulations for each of the scenarios were analyzed using these metrics to measure the environmental consequences of the proliferation of AI infrastructure. A comparative analysis was then conducted to compare the electricity demand, carbon emissions, renewable energy usage, operational efficiency, and overall trajectory to Net-Zero goals across the various AI growth paths.

5.5 Model Validation

The outputs from the proposed simulation framework were qualitatively checked against recent reports and published work on the energy use and carbon emission in Data Center using AI. The validation was limited to ensuring that the estimated electricity demand, carbon emissions projections and renewable energy share were within realistic bounds as reported by internationally recognized organizations and recent scientific literature. The proposed framework was not intended to replicate the results of a particular study, but to provide estimates that are consistent with available statistics and longer-term energy projections. This validation process enhances the trust in the simulation and retains the flexibility of the proposed AI development assessment framework in Python. Model validation criteria are given in Table IX.

TABLE IX. MODEL VALIDATION CRITERIA

Validation Aspect	Validation Method
Electricity Demand	Compared with published global energy projections
Carbon Emissions	Compared with reported emission trends in recent literature
Renewable Energy Share	Compared with international renewable energy statistics
PUE	Verified against industry benchmark values
Overall Trends	Checked for consistency with previous sustainability studies

6. RESULTS AND DISCUSSION

6.1 Annual Electricity Demand Analysis

One of the primary metrics used to assess the sustainability footprint of Generative AI data centers is their electricity demand, which reflects their future energy needs and affects their related environmental impacts. The annual electricity demand of the AI data centers is therefore simulated in 4 scenarios for the AI data center development until 2050.

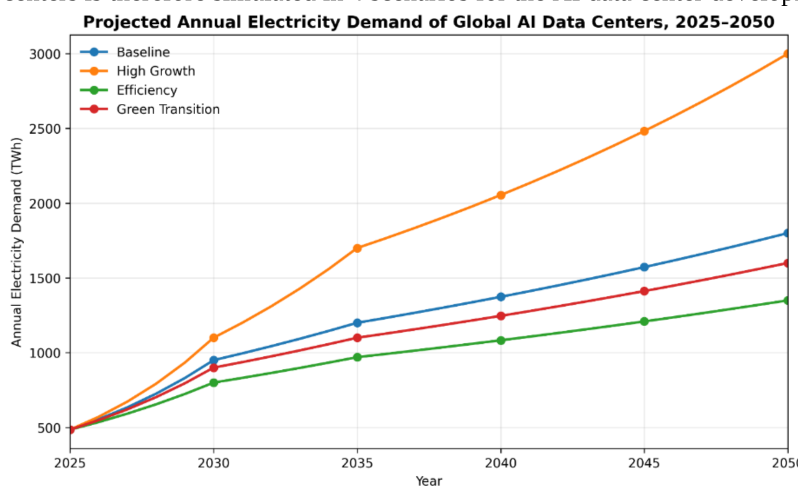

Fig. 2. Projected Annual Electricity Demand of Global AI Data Centers under the Four Simulation Scenarios (2025–2050).

The electricity consumption trend will continue to increase for all scenarios as shown in Figure 2, due to the expected increase in AI services and computing demands. But there are some significant differences when it comes to AI growth rate and operational efficiencies. The High Growth scenario shows the highest electricity demand, rising from 485 TWh in 2025 to around 3000 TWh by 2050, reflecting the high electricity usage of the rapid growth of AI infrastructure. The Baseline scenario approaches a level of energy usage of around 1800 TWh, an energy demand that is moderately high. The lowest electricity demand in 2050 (1350 TWh) corresponds to the so-called Efficiency scenario, which is based on increasing efficiency of the data centers as well as on reducing the PUEs and optimized usage of computing resources. By enabling sustainable infrastructure development, the Green Transition scenario brings energy growth to around 1600 TWh, while keeping AI adoption going. In summary, the findings suggest that enhancing the efficiency of the operation is a key factor in managing the future power consumption of AI data centers. While the use of renewable energy is a critical step in minimizing environmental effects, one of the best ways to cap energy increases is through efficiency. The next subsection will be used to explore how these electricity demand trends manifest in future carbon emission trends.

6.2 Carbon Emission Analysis

Chief among the metrics for assessing the environmental sustainability of Generative AI data centers is carbon emissions, which directly correlate with the environmental impacts of growing electricity use. Based on the forecast electricity demand and the carbon intensities for each scenario, the proposed simulation model calculates the annual CO_2 emissions for each development scenario from 2025 to 2050.

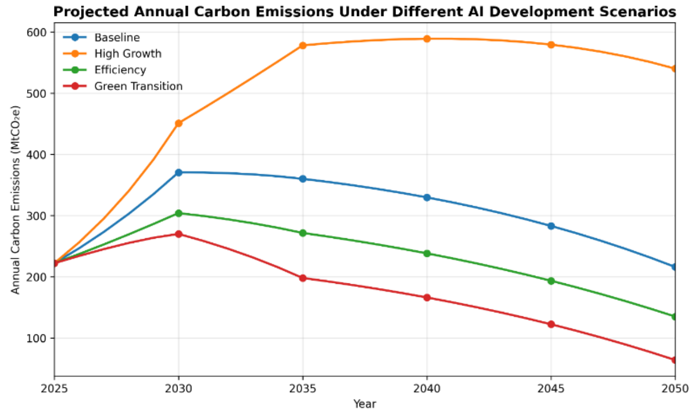

Fig. 3. Projected Annual Carbon Emissions of Global AI Data Centers under Different Development Scenarios (2025–2050).

As shown in Figure 3, in spite of the steady increase in AI infrastructure, carbon emissions have a clear trend in each of the four scenarios. The High Growth scenario results in the peak emissions during the simulation period of around 540 $MtCO_2e$ by 2050. The high electricity demand growth is the major driver for this outcome, and relative to decarbonization of electricity, the improvements have not been as significant. In the Baseline scenario, annual emissions around 216 $MtCO_2e$ are projected in 2050, which corresponds to moderate growth in AI use, based on existing energy transition patterns. The Efficiency scenario shows the reduction in annual emissions, which falls to around 135 $MtCO_2e$, and so shows that operational efficiency improvements can make a sizeable contribution to reducing environmental impacts by reducing electricity consumption.

The Green Transition scenario is the one that results in the smallest annual carbon emissions of 64 $MtCO_2e$ by 2050 of all the scenarios investigated. The electricity demand continued to rise, but the impact of the progressive decrease in the electricity carbon intensity and the increased share of renewable energy sources more than compensated for the impact of AI infrastructure expansion. In conclusion, these findings show that decarbonizing electricity demand is not enough to meet longer term climate targets. Rather, energy-efficient data center operation and rapid electricity decarbonization offers the best approach to reducing carbon emissions in the future. The following subsection examines the role of renewable energy integration and enhancements in data center operational efficiency toward these environmental benefits.

6.3 Renewable Energy Contribution and Operational Efficiency Analysis

The integration of renewable energy and optimizing its use are important factors that impact the environmental sustainability of AI data centers. The carbon intensity of power generation can be lowered by using renewable electricity resources, and the amount of electricity that is needed to support computational workloads can be reduced by improving Power Usage Effectiveness (PUE). Based on this, this subsection analyses the changes in renewable energy contribution and PUE expected in the four simulation scenarios.

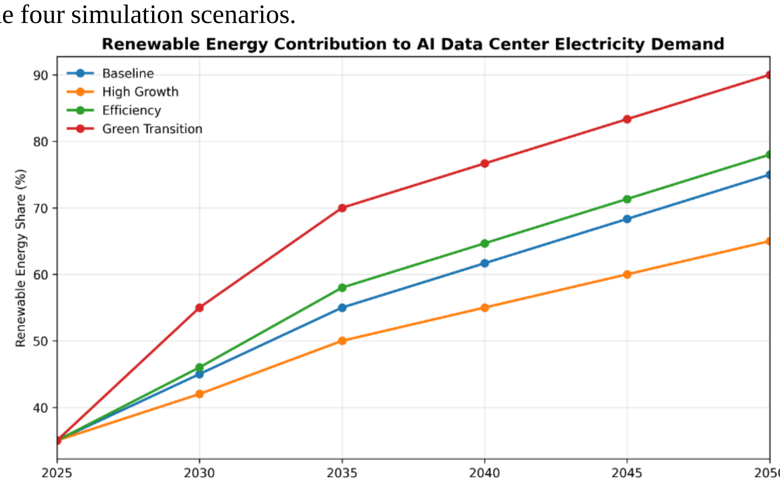

Fig. 4(a). Renewable Energy Share under Different AI Development Scenarios (2025–2050).

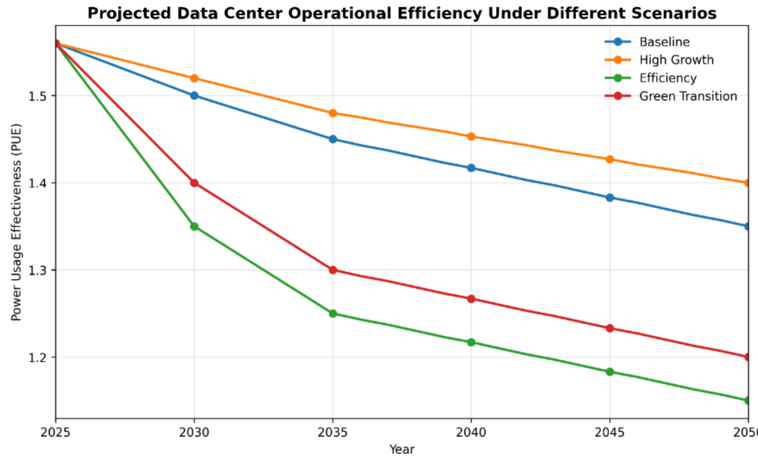

Fig. 4(b). Projected Power Usage Effectiveness (PUE) under Different AI Development Scenarios (2025–2050).

In all scenarios, the renewable energy share has a consistent increasing trend during the simulation period as illustrated in Figure 4(a). The lowest level of renewable energy uptake (65%) is found in the High Growth scenario, while the highest (close to 90%) is in the Green Transition scenario; under the High Growth scenario electricity demand grows faster than renewable energy is installed. The Baseline and Efficiency scenarios achieve around 75% and 78%, respectively, putting them in the middle of cleaner electricity generation.

Likewise, Figure 4(b) illustrates that the operational efficiency is continually enhancing over time. In the Efficiency scenario, the PUE of the data center will reach its lowest level (1.15) by 2050, with the Green Transition scenario coming next (1.20), showing substantial savings of energy overheads with the use of better cooling equipment and optimized data center management. However, these PUE values (1.35 for Baseline, 1.40 for High Growth) are higher than the values found in other studies, indicating less progress in the efficiency of the infrastructure.

Finally, the overall results indicate that both the use of renewables and operational efficiency can be complementary strategies to increase the sustainability of AI infrastructure. The one primary benefit of increasing the amount of renewable energy is to reduce the indirect carbon footprint but the saving from PUE improvements is direct saving of electric consumption, which must be accompanied by an increase in renewable energy as part of a strategy to achieve the future Net-Zero goals. The effects of these improvements on the overall Net-Zero performance of the proposed scenarios is analysed in this section.

6.4 Net-Zero Performance Assessment

The quest for “Net-Zero” emissions has become a key priority for both governments and tech giants, as they both strive to reduce the environmental footprint of the expanding AI infrastructure.The concept of “Net-Zero” is a major ambition for governments and tech giants alike, both seeking to lower the environmental impact of the rapidly growing AI infrastructure. The proposed simulation framework uses the Net-Zero Gap Index (NZGI) to assess the success of each development pathway to the objective, and measures the gap between the carbon emissions projected from each pathway and the path towards the target emissions.

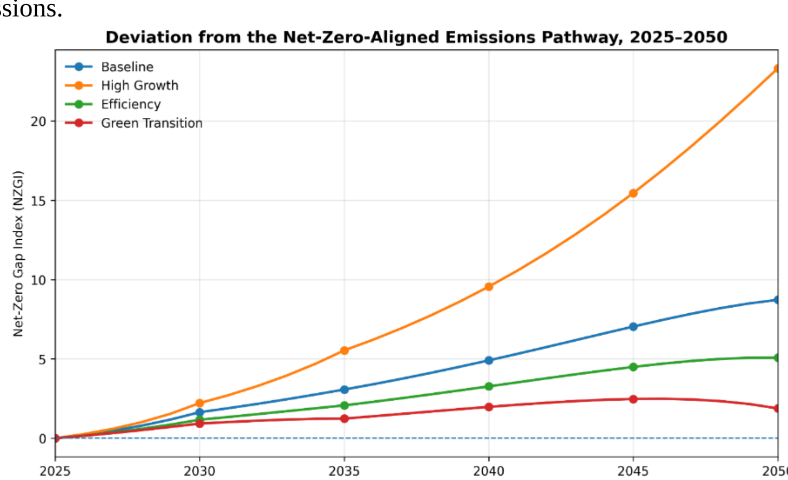

Fig. 5. Net-Zero Gap Index (NZGI) under Different AI Development Scenarios (2025–2050).

In the High Growth scenario, as illustrated in Figure 5, there is the greatest difference from the Net-Zero pathway over the simulation period, with an NZGI of 23.31 in 2050. The result shows that the rate of growth of AI infrastructure, coupled with relatively low rates of decarbonization for electricity generation and operational efficiency, creates a huge Δ between actual emissions and long-term climate goals.
The NZGI level for the Baseline scenario is 8.72, which indicates moderate work towards emission reduction, but is still well off the path to Net-Zero. The Efficiency scenario further enhances environmental performance by lowering the electricity demand and operational efficiency, which brings the index down to 5.08. The Green Transition scenario is the most successful at achieving the goals of achieving Net-Zero, with the lowest NZGI value of 1.88 in 2050 of all the scenarios investigated. While this scenario does not fully close the emission gap, it significantly reduces the gap between the trajectory to this pathway and the target pathway due to high renewable energy share and lower electricity carbon intensity.
The results overall show that there is no single solution to the Net-Zero goals. Rather, the best way to mitigate the future environmental impacts is to integrate energy-efficient AI infrastructure with massive-scale renewable energy generation. The results suggest that while electric vehicle charging infrastructure is a vital element for sustainable AI development, it is not a solution alone, and coordinated efforts are needed to improve energy efficiency, decarbonize electricity, and plan charging infrastructure. The comparative evaluation of all the simulation scenarios is summarized in the following subsection, to determine the overall strengths and weaknesses of each development pathway.

6.5 Comparative Evaluation of AI Development Scenarios

A detailed study of the four simulated scenarios was carried out to determine which is the most sustainable future development route for Generative AI data centers. The comparison takes into account all sustainability indicators evaluated, such as annual electricity consumption, carbon emissions, cumulative emissions, renewable energy contribution, operational efficiency and Net-Zero Gap Index (NZGI), which gives an overall picture of the environmental performance of each scenario.

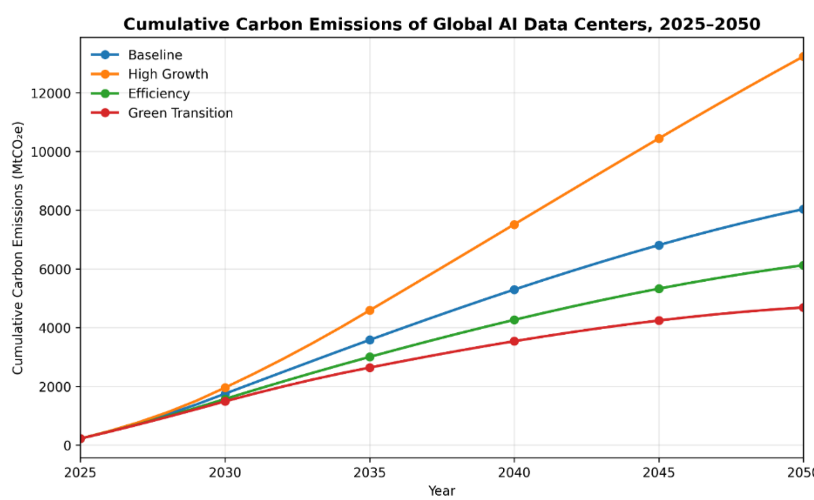

Fig. 6. Cumulative Carbon Emissions of Global AI Data Centers under Different Development Scenarios (2025–2050).

TABLE X. COMPARATIVE SUSTAINABILITY PERFORMANCE OF THE FOUR SIMULATION SCENARIOS IN 2050.

Scenario	Demand (TWh)	Annual Emissions ($MtCO_2e$)	Cumulative Emissions ($MtCO_2e$)	Renewable Share	PUE	NZGI
Baseline	1800	216	8035.37	75%	1.35	8.724
Efficiency	1350	135	6125.80	78%	1.15	5.077
Green Transition	1600	64	4686.53	90%	1.20	1.881
High Growth	3000	540	13234.70	65%	1.40	23.310

Fig. 6 shows large variations between the simulated scenarios in terms of cumulative environmental effects over the simulation period 2025–2050. The largest cumulative carbon emissions (13,234.70 $MtCO_2e$) result from the interplay of faster growth of electricity demand and lower electricity supply decarbonisation rates in the Higher Growth scenario. In comparison, the Green Transition scenario has the lowest cumulative emissions (4,686.53 $MtCO_2e$), highlighting how the use of renewable energy and gradual decarbonisation of energy intensity can help minimize long-term environmental impacts.
The results from the comparisons summarized in Table X also demonstrate the assets and challenges of each development path. The Green Transition scenario yield the lowest electricity demand (1350 TWh) and the highest operational efficiency

(PUE = 1.15), but at the same time the lowest annual carbon emissions (64 $MtCO_2e$), highest renewable energy contribution (90%) and the smallest Net-Zero Gap Index (1.88). The opposite is true for the High Growth scenario where the least favorable sustainability performance is recorded in all categories, the highest electricity demand (3000 TWh), annual emissions (540 $MtCO_2e$), cumulative emissions (13,234.70 $MtCO_2e$) and NZGI (23.31).
The results have shown that these objectives cannot be made through a single sustainability strategy. Both operational efficiency and penetration of renewables are key ways to reduce electricity demand, with efficiency the most immediate, and carbon emission reduction the most direct. The most sustainable AI infrastructure is realized by combining both strategies in a cohesive development process. In general, the comparative impact assessment indicates that the Green Transition scenario offers the most balanced environmental performance across all scenarios, and the High Growth scenario is more difficult for future Net-Zero commitments. The results highlight the importance of establishing energy efficiency policies that are coordinated to both accelerate the decarbonisation of electricity and promote the adoption of energy-efficient data center technologies, bringing up the sustainable development of Generative AI infrastructure.

7. CONCLUSION

The study used a Python simulation model to evaluate the sustainability of Generative AI data centers under four scenarios of development from 2025 to 2050. The proposed framework considered the impact of the expansion of AI infrastructure on the environment using various sustainability metrics: annual electricity demand, carbon emissions, contribution of renewable energy sources, Power Usage Effectiveness (PUE), cumulative emissions and the Net-Zero Gap Index (NZGI). The framework integrates publicly accessible energy and environmental data, simulation with scenarios and provides a helpful instrument for solving future energy and climate issues with the support of AI. The simulation outcomes show the environmental performance of AI data centers is hugely reliant on the future infrastructure development strategies. The High Growth scenario showed the largest electricity demand, carbon emissions, cumulative emissions, and Net-Zero Gap Index, suggesting that the rapid growth of AI without any significant gains in efficiency or decarbonization of electricity use could have a significant impact on environmental pressure. The Green Transition scenario, on the other hand, by implementing both high renewable energy share and low electricity carbon intensity score, had the best overall environmental score and the lowest carbon footprint, and the closest to the Net-Zero targets, owing to continuous efficiency improvements. The results additionally show that there is no one specific mitigation strategy to ensure sustainable AI development. Improving the operational efficiency and significantly reducing carbon emissions by the deployment of renewables are very effective ways of reducing electricity demand. So, it's crucial to combine both strategies for a balanced and sustainable approach to AI technological development and long-term climate objectives. The framework is a transparent, reproducible and computationally efficient tool which could be used by researchers, policymakers and industry stakeholders to consider the environmental sustainability of future AI infrastructure. The modularity and scenario specific implementation make it easy for adaptation to different regions and electricity systems as well as different paths of AI development. Future studies will continue with the development of the proposed framework which will include real-time electricity market data, regional energy mixes, dynamic carbon pricing and life-cycle assessment of AI hardware. Further, incorporating optimization techniques and machine learning models for energy demand forecasting may further enhance the precision of long-term sustainability evaluations and enable better policy decisions for global Net-Zero targets.

Funding:

This research was not funded by any institution, foundation, or commercial entity. All expenses related to the study were managed by the authors.

Conflicts of Interest:

The authors declare that there are no conflicts of interest to disclose.

Acknowledgment:

The authors wish to acknowledge their institutions for their instrumental support and encouragement throughout the duration of this project.

References

[1] J. Wen, R. Zhang, D. Niyato, J. Kang, H. Du, Y. Zhang, and Z. Han, "Generative AI for low-carbon artificial intelligence of things with large language models," IEEE Internet of Things Magazine, vol. 8, no. 1, pp. 82–91, 2024.
[2] L. de Roucy-Rochegonde and A. Buffard, AI, Data Centers and Energy Demand. Paris, France: Institut Français des Relations Internationales (IFRI), 2025.
[3] A. d'Orgeval, E. Assoumou, V. Sessa, I. Colak, S. Sheehan, and Q. Avenas, "Carbon footprint of AI data centers: A life cycle approach," in Proc. 16th Int. Conf. Applied Energy, Sep. 2024, pp. 112–123.
[4] H. Lee et al., "Climate Change 2023: Synthesis Report, Summary for Policymakers," in Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Geneva, Switzerland: Intergovernmental Panel on Climate Change (IPCC), 2023, pp. 1–34.
[5] A. Faiz, S. Kaneda, R. Wang, R. Osi, P. Sharma, F. Chen, and L. Jiang, "LLMCarbon: Modeling the end-to-end carbon footprint of large language models," in Proc. Int. Conf. Learning Representations (ICLR), pp. 24727-24741, May 2024.

[6] A. Shehabi et al., 2024 United States Data Center Energy Usage Report. Berkeley, CA, USA: Lawrence Berkeley National Laboratory, 2024.
[7] K. M. U. Ahmed, M. H. J. Bollen, and M. Alvarez, "A review of data centers energy consumption and reliability modeling," IEEE Access, vol. 9, pp. 152536–152563, 2021.
[8] J. Mah, A. Aquino, D. Ghosh, and A. Hoffmeister, 2025 International Energy Efficiency Scorecard. Washington, DC, USA: American Council for an Energy-Efficient Economy (ACEEE), 2025.
[9] L. F. Enriquez-Contreras, S. M. Shafiul Alam, M. J. Culler, K. G. Cafferty, J. M. Tacke, and H. Ackenhusen, Bridging the Gap for Powering Data Centers, Rep. INL/RPT-26-89901. Idaho Falls, ID, USA: Idaho National Laboratory, 2025.
[10] P. Hungry and H. A. W. D. E. Demand, "Commodity special feature: Online Annex 1.1," World Economic Outlook, 2025.
[11] J. Glassmire, H. Bitaraf, S. Papadakis, and A. Oudalov, "Accelerating data center decarbonization and maximizing renewable usage with grid edge solutions," in Proc. Design, Automation & Test in Europe Conf. (DATE), pp. 288–293, Feb. 2021.
[12] A. Shehabi, S. J. Smith, E. Masanet, and J. Koomey, "Data center growth in the United States: Decoupling the demand for services from electricity use," Environmental Research Letters, vol. 13, no. 12, Art. no. 124030, 2018.
[13] E. Asmelash and R. Gorini, International Oil Companies and the Energy Transition. Abu Dhabi, United Arab Emirates: International Renewable Energy Agency (IRENA), 2021.
[14] S. Pimenow, O. Pimenowa, and P. Prus, "Challenges of artificial intelligence development in the context of energy consumption and impact on climate change," Energies, vol. 17, no. 23, Art. no. 5965, 2024.
[15] A. de Vries, "The growing energy footprint of artificial intelligence," Joule, vol. 7, no. 10, pp. 2191–2194, 2023.
[16] Johnson, N., McGirr, A., Hatton, L., Bamisile, O., Rooney, A. R., & Staffell, I. Energy Strategy Reviews.