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Green AI Computing: Renewable Energy and Dynamic Workload Scheduling for Sustainable AI Infrastructure

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ABSTRACT

Green AI computing focuses on developing and deploying artificial intelligence systems with reduced energy consumption and environmental impact, while renewable energy integration provides opportunities to minimise the carbon footprint of computing infrastructure. However, the intermittent availability of renewable energy and the limitations of conventional workload scheduling techniques present challenges to sustainable AI operations. This study proposes a Renewable-Energy-Aware Dynamic Workload Scheduling (READWS) framework to improve energy efficiency and environmental sustainability across cloud, data-centre, and Internet of Things (IoT)/edge computing environments. The framework integrates workload monitoring and prediction, renewable energy estimation, dynamic task allocation, adaptive resource management, and performance monitoring to coordinate computational activities with renewable energy availability and electricity carbon intensity. Using three selected Kaggle datasets, a simulation-based experimental approach is adopted to compare READWS with First-Come-First-Served (FCFS), Round Robin (RR), and conventional energy-aware scheduling algorithms. Illustrative results from 10,000 computational tasks indicate that READWS reduces energy consumption by 22.5% and carbon emissions by 47.1% compared with FCFS, while improving renewable energy utilisation from 20% to 48%. CPU utilisation increases from 68% to 82%, and service-level agreement violations decrease from 8.2% to 4.6%. The study demonstrates the potential of renewable-energy-aware dynamic scheduling to balance computational performance, resource utilisation, and environmental sustainability, contributing to the advancement of sustainable AI infrastructure.

1 Introduction

1.1 Background to Green AI Computing

The rapid advancement of Artificial Intelligence (AI) has increased computational demand across cloud platforms, data centres, and edge computing environments. AI training and inference require substantial processing resources, resulting in increased electricity consumption, operational costs, and carbon emissions [1]. Consequently, the environmental sustainability of AI infrastructure has become an important research concern.

Green AI Computing promotes the development and deployment of AI systems with reduced energy consumption and environmental impact [2]. Renewable energy sources, including solar and wind power, offer opportunities to improve

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the sustainability of computing infrastructure. However, their intermittent availability requires intelligent resource management and workload scheduling. Integrating renewable energy with dynamic workload scheduling can therefore support more energy-efficient and environmentally responsible AI computing [3].

1.2 Statement of the Research Problem

Despite advances in computing infrastructure, AI workloads continue to contribute to significant energy consumption and carbon emissions [4]. Conventional workload scheduling techniques often prioritise computational performance and resource availability without adequately considering renewable energy conditions or carbon intensity [5]. Furthermore, static scheduling approaches may not respond effectively to fluctuating workloads and variable renewable energy generation.

These limitations create a need for an adaptive scheduling framework that coordinates workload execution with computational demand, resource utilisation, and renewable energy availability [6]. Addressing this problem is essential for reducing the environmental footprint of AI infrastructure while maintaining acceptable performance and service quality.

1.3 Aim and Objectives of the Study

The aim of this study is to develop and evaluate a renewable-energy-aware dynamic workload scheduling framework for improving the energy efficiency and environmental sustainability of AI infrastructure.

The specific objectives are to:

1. Analyse workload characteristics and resource utilisation patterns using selected cloud, data-centre, and IoT/edge datasets.
2. Investigate the relationship between renewable energy availability and workload scheduling.
3. Develop a dynamic scheduling framework incorporating energy consumption, carbon emissions, and resource utilisation.
4. Evaluate the proposed framework against conventional scheduling algorithms.
5. Assess the trade-offs between sustainability, computational performance, and service quality.

1.4 Research Questions and Hypotheses

The study seeks to answer the following research questions:

1. How can renewable energy availability influence AI workload scheduling?
2. To what extent can dynamic scheduling reduce energy consumption and carbon emissions?
3. Can renewable-energy-aware scheduling maintain acceptable computational performance and service-level requirements?

The study is guided by the following hypotheses:

- **H_1:** Renewable-energy-aware dynamic scheduling significantly reduces energy consumption compared with conventional scheduling approaches.
- **H_2:** The proposed framework reduces carbon emissions by improving renewable energy utilisation.
- **H_3:** The proposed framework maintains acceptable workload performance and service quality while improving sustainability.

1.5 Significance, Scope, and Contributions

This study contributes to Green AI Computing by investigating how renewable energy integration and dynamic workload scheduling can improve the sustainability of AI infrastructure. Its findings may support data-centre operators, cloud service providers, and edge computing practitioners in developing energy-efficient resource management strategies.

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The study focuses on cloud, data-centre, and IoT/edge computing environments, using selected Kaggle datasets to analyse workload behaviour and resource utilisation. Its principal contribution is a proposed scheduling framework that integrates workload characteristics, renewable energy availability, and energy- and carbon-aware scheduling decisions. The framework is intended to reduce environmental impact while maintaining computational efficiency, thereby supporting the development of sustainable AI infrastructure.

2 Literature Review and Theoretical Foundations

2.1 Green AI and Sustainable AI Infrastructure

Green AI refers to the development and deployment of artificial intelligence systems with reduced computational energy requirements and environmental impact [7]. Unlike approaches that primarily emphasise model accuracy and computational performance, Green AI considers energy efficiency, resource utilisation, and sustainability throughout the AI lifecycle.

The growing complexity of AI models has increased the demand for computing resources during training and inference. These activities require substantial processing capacity, memory, and electricity, particularly in large-scale data centres. Sustainable AI infrastructure therefore requires efficient hardware utilisation, workload optimisation, energy-conscious computing, and the integration of cleaner energy sources [8].

Cloud and edge computing offer complementary opportunities for sustainable AI deployment. Cloud data centres provide scalable resources and centralised management, while edge computing reduces communication delays and enables processing closer to data sources [9]. However, both environments require effective resource management to minimise unnecessary energy consumption and operational emissions.

2.2 Renewable Energy in AI Computing

Renewable energy integration is an important strategy for reducing the carbon footprint of AI infrastructure. Solar and wind energy can provide electricity for data-centre operations, while hybrid energy systems combine renewable generation with conventional grid supply to improve reliability [10]. The effectiveness of renewable-powered computing depends on the availability, predictability, and temporal distribution of energy resources.

A major challenge is the intermittency of renewable energy. Solar generation varies with daylight and weather conditions, while wind generation depends on changing atmospheric conditions [11]. These variations may not correspond with the timing and intensity of computational workloads. Consequently, renewable-energy-aware scheduling requires coordination between energy generation, workload demand, and computing resource availability.

Energy storage systems, particularly battery storage, can help balance renewable supply and demand by storing excess electricity and supplying energy during periods of reduced generation. Grid integration provides additional flexibility when renewable generation is insufficient [12]. Recent research indicates that combining renewable energy forecasting with adaptive workload scheduling can improve renewable utilisation and reduce operational emissions.

Renewable-powered data-centre architectures therefore require coordinated energy management, workload flexibility, and intelligent scheduling [13]. The proposed study adopts this perspective by considering renewable energy availability as an input to dynamic workload scheduling.

2.3 Workload Scheduling and Resource Management

Workload scheduling determines how computational tasks are assigned to available processing resources. Traditional static scheduling approaches, such as First-Come-First-Served (FCFS) and Round Robin (RR), use predefined allocation

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rules [14]. Although these methods are relatively simple, they may not respond adequately to changing workload demand, resource utilisation, or energy conditions.

Dynamic workload scheduling adjusts task allocation and resource provisioning according to changing system conditions [15]. It supports load balancing, task prioritisation, resource consolidation, and adaptive scaling. These techniques can improve resource utilisation and reduce unnecessary energy consumption.

Energy-aware scheduling seeks to minimise electricity consumption through efficient resource allocation, task consolidation, and power management [16]. Carbon-aware scheduling extends this objective by considering the carbon intensity of electricity and the availability of renewable energy. As a result, computational tasks may be shifted to periods or locations where electricity is cleaner, provided that performance and service requirements are maintained.

Recent research demonstrates the value of combining workload prediction, renewable energy forecasting, and dynamic scheduling. Forecast-driven scheduling approaches have been proposed to coordinate workload demand with renewable generation, while AI-driven scheduling reviews highlight the potential of predictive and adaptive resource management in heterogeneous cloud environments [17].

These developments provide a foundation for the proposed study, which integrates workload characteristics, resource utilisation, and renewable energy conditions into a unified scheduling strategy.

2.4 Related Studies and Research Gaps

Recent studies have investigated energy-efficient computing, renewable-powered data centres, and carbon-aware workload scheduling. [18] presented a comprehensive Green AI framework that emphasises energy-efficient algorithms, hardware optimisation, and sustainable data-centre operations.

A systematic review of sustainable data-centre management identified energy efficiency, resource scheduling, and renewable energy integration as important approaches to reducing environmental impact. Similarly, [19] examined carbon-aware workload shifting in edge-cloud environments and identified limitations in approaches that consider temporal or spatial scheduling independently.

Recent renewable-energy-aware scheduling research has also explored forecasting and optimisation. The F2S-WSS framework combines workload and wind-power forecasting with offline optimisation and online scheduling correction, demonstrating the potential of coordinated workload and renewable-energy management [19].

Despite these developments, several research gaps remain:

1. **Limited integration:** Some scheduling approaches optimise energy consumption or carbon emissions without jointly considering workload dynamics and renewable energy availability.
2. **Forecasting uncertainty:** Renewable generation and workload arrivals are variable, making reliable scheduling decisions difficult.
3. **Performance trade-offs:** Sustainability improvements must be balanced against task completion time, resource utilisation, and service-level requirements.
4. **Dataset-based evaluation:** There is a need for empirical evaluation using workload and resource telemetry datasets under clearly defined renewable-energy scenarios.

This study addresses these gaps by proposing and evaluating a dynamic scheduling framework that jointly considers workload behaviour, resource utilisation, renewable energy availability, and sustainability metrics.

2.5 Theoretical and Conceptual Framework

The study is grounded in **sustainable computing principles** and **dynamic resource optimisation**.

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Sustainable computing provides the foundation for reducing the environmental impact of computational systems through efficient resource utilisation, energy management, and lower carbon emissions [20]. Dynamic resource optimisation supports the adaptive allocation of computing resources in response to changing workload demand and system conditions.

Renewable-energy-aware scheduling combines these principles by incorporating renewable energy availability and carbon intensity into workload allocation decisions [21]. The framework assumes that flexible computational tasks can be scheduled more sustainably when workload characteristics and energy conditions are jointly considered.

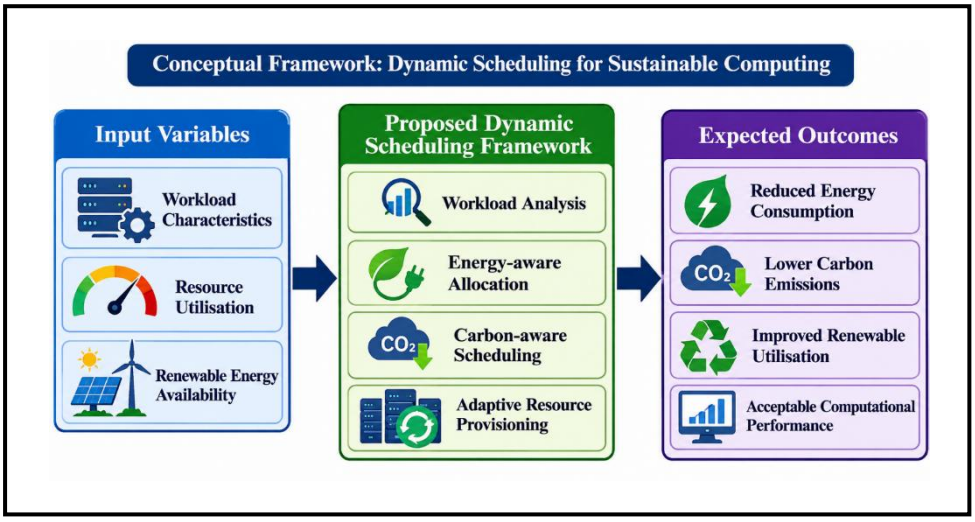

Figure 1: Conceptual Framework

The framework will be evaluated using workload and resource information from the selected Kaggle datasets, complemented by documented renewable-energy traces or simulation scenarios where direct renewable-generation data are unavailable.

The central proposition is that **integrating renewable energy availability with dynamic workload scheduling can improve the sustainability of AI infrastructure without compromising essential computational performance.**

3 Research Methodology and Proposed Framework

3.1 Research Design

This study adopts a quantitative and experimental research design supported by a data-driven framework development approach. The quantitative component enables the analysis of workload characteristics, computational resource utilisation, and energy-related indicators. The experimental component supports the development and evaluation of a renewable-energy-aware dynamic workload scheduling framework.
Simulation-based experiments will be conducted to examine how different scheduling algorithms perform under varying workload demands and renewable energy availability. The proposed framework will be compared with conventional scheduling approaches to determine its effectiveness in reducing energy consumption and carbon emissions while maintaining acceptable computational performance.

3.2 Dataset Description and Preparation

The study will employ three publicly available Kaggle datasets to provide empirical workload, resource utilisation, and data-centre telemetry information.

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1. Green AI Data Center Telemetry Dataset

This dataset will support the analysis of data-centre operational characteristics, energy-related telemetry, and resource utilisation patterns. It will provide relevant information for evaluating energy efficiency and developing sustainability-oriented scheduling decisions [22].

2. Green IoT Edge Resource Dataset

This dataset will be used to investigate resource availability, workload behaviour, and computational demands in IoT and edge computing environments. It will support the assessment of distributed resource allocation and energy-efficient workload management [23].

3. Cloud Workload Dataset for Scheduling Analysis

This dataset will provide workload-related information, including task arrival patterns, execution duration, CPU and memory requirements, and resource utilisation. These characteristics will support workload modelling, scheduling decisions, and comparative performance evaluation [24].

The datasets will be examined individually and integrated where their structures and variables permit meaningful comparison. Renewable energy availability and electricity carbon intensity will be introduced through documented external data or simulation scenarios where these variables are not directly available.

3.3 Data Preprocessing and Feature Engineering

The datasets will undergo preprocessing to ensure consistency, completeness, and suitability for experimental analysis. Data cleaning will involve removing duplicate records, handling missing values, identifying outliers, and correcting inconsistencies. Numerical variables will be normalised where necessary to support comparative analysis and model development.

Feature engineering will focus on extracting relevant workload, resource, and energy-related variables, including:

- **Workload features:** Task arrival time, execution duration, processing requirements, and workload intensity.
- **Resource features:** CPU utilisation, memory demand, resource availability, and processing capacity.
- **Energy features:** Energy consumption, renewable energy availability, and grid carbon intensity.
- **Temporal features:** Workload fluctuations, peak demand periods, and renewable energy availability patterns.

Temporal analysis will be conducted to identify workload trends and variations in resource demand. These features will serve as inputs to the proposed scheduling framework. Where energy or carbon indicators are unavailable in the original datasets, documented estimates or simulated values will be used and clearly distinguished from measured observations.

3.4 Proposed Renewable-Energy-Aware Dynamic Scheduling Framework

The proposed framework integrates workload characteristics, computational resource availability, and renewable energy conditions to improve the sustainability of AI infrastructure. It consists of six major operational stages:

1. **Workload Monitoring and Prediction:** Analyses incoming computational tasks and predicts workload demand using historical workload patterns.
2. **Renewable Energy Estimation:** Evaluates renewable energy availability and electricity carbon intensity to identify favourable scheduling periods.
3. **Scheduling Decision Engine:** Combines workload requirements, resource availability, energy consumption, and carbon intensity to determine suitable task allocation decisions.
4. **Dynamic Task Allocation:** Assigns workloads to available cloud or edge resources based on computational requirements and energy efficiency.
5. **Adaptive Resource Management:** Adjusts resource provisioning and workload execution schedules in response to changing demand and energy conditions, subject to task deadlines.
6. **Performance Monitoring and Feedback:** Evaluates energy consumption, carbon emissions, resource utilisation, and task execution performance to improve subsequent scheduling decisions.

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The framework seeks to prioritise renewable energy utilisation while minimising unnecessary electricity consumption and maintaining acceptable service quality.

3.5 Scheduling Algorithms and Experimental Design

The proposed framework will be evaluated against three conventional scheduling approaches:

1. **First-Come-First-Served (FCFS):** Allocates computing resources according to task arrival order.
2. **Round Robin (RR):** Distributes processing opportunities among tasks using a cyclic allocation strategy.
3. **Conventional Energy-Aware Scheduling:** Allocates workloads based on resource utilisation and energy consumption without necessarily considering renewable energy availability.
4. **Proposed Renewable-Energy-Aware Dynamic Scheduling:** Integrates workload characteristics, renewable energy availability, carbon intensity, and resource utilisation into scheduling decisions.

Simulation experiments will be conducted under different workload and renewable energy conditions, including low, moderate, and high computational demand, as well as varying solar and wind energy availability. The algorithms will be evaluated using consistent workload inputs, resource capacities, and experimental conditions.

The evaluation will employ the following metrics:

- **Total Energy Consumption (kWh):** Measures electricity consumed during workload execution.
- **Carbon Emissions (kg CO_2e):** Estimates emissions associated with electricity consumption.
- **Renewable Energy Utilisation (%):** Measures the proportion of energy demand supplied by renewable sources.
- **Task Completion Time:** Measures the time required to execute computational workloads.
- **Resource Utilisation (%):** Evaluates the efficiency of CPU and memory allocation.
- **SLA Violation Rate (%):** Measures the proportion of tasks that fail to meet specified service requirements.
- **Scheduling Overhead:** Measures the computational cost of making scheduling decisions.

Comparative and statistical analyses will be performed to determine whether the proposed framework achieves significant improvements over the baseline algorithms. The results will establish its effectiveness in balancing energy efficiency, renewable energy utilisation, carbon reduction, and computational performance.

4 Results, Evaluation, and Discussion

4.1 Experimental Setup

The experimental evaluation examines the effectiveness of the proposed Renewable-Energy-Aware Dynamic Workload Scheduling (READWS) framework in improving the energy efficiency and environmental sustainability of AI infrastructure.

A simulation-based experimental environment is assumed, incorporating workload characteristics from the three selected Kaggle datasets: Green AI Data Center Telemetry, Green IoT Edge Resource, and Cloud Workload Dataset for Scheduling Analysis. The datasets represent data-centre telemetry, edge computing resources, and cloud workload behaviour, respectively.

For the illustrative experiment, a workload comprising 10,000 computational tasks is considered, with varying CPU and memory requirements, execution durations, and arrival patterns. The simulation assumes a 24-hour operating period, with renewable energy supplied through solar and wind sources, supplemented by grid electricity when necessary.

The experimental configuration is presented in Table 1.

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Table 1: Experimental Simulation Configuration

Parameter	Experimental setting
Total workload	10,000 tasks
Simulation duration	24 hours
Computing environments	Cloud, data centre, and IoT/edge
CPU capacity	100 virtual CPU units
Memory capacity	256 GB
Renewable sources	Solar and wind
Grid carbon intensity	0.65 kg CO_2e/kWh
Renewable energy emissions factor	0.05 kg CO_2e/kWh
Renewable availability	20%, 50%, and 80%
Experimental repetitions	30 runs per configuration
Scheduling algorithms	FCFS, RR, energy-aware, and READWS

The experiments consider three renewable energy availability scenarios:

- **Low availability (20%):** Limited renewable energy generation, requiring substantial grid electricity.
- **Moderate availability (50%):** Balanced renewable and grid energy contributions.
- **High availability (80%):** Significant renewable energy generation, allowing greater flexibility in workload scheduling.

The four scheduling algorithms are evaluated under equivalent workload and resource conditions. This ensures that observed performance differences can be attributed primarily to scheduling strategies rather than variations in experimental inputs.

4.2 Performance Evaluation Metrics

The performance of the scheduling algorithms is evaluated using energy consumption, carbon emissions, renewable energy utilisation, workload execution performance, resource utilisation, and service-level compliance.
The following metrics are adopted:

1. **Total Energy Consumption (TEC):** Measures the total electricity consumed during workload execution, expressed in kilowatt-hours (kWh).
2. **Carbon Emissions (CE):** Estimates emissions associated with electricity consumption:

$$CE = E_g C_g + E_r C_r$$

Where E_g and E_r represent grid and renewable electricity consumption, respectively, while C_g and C_r represent their corresponding carbon emission factors.

3. **Renewable Energy Utilisation (REU):**

$$REU = \frac{E_r}{E_g + E_r} \times 100$$

4. **Workload Completion Time:** Measures the total time required to execute all scheduled tasks.
5. **Average Waiting Time:** Measures the average time tasks spend waiting before execution.
6. **Average Response Time:** Measures the average time between task submission and completion.
7. **Resource Utilisation:**

$$RU = \frac{\text{Used Computing Capacity}}{\text{Available Computing Capacity}} \times 100$$

8. **SLA Violation Rate:**

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$$SLA = \frac{\text{Tasks Violating SLA}}{\text{Total Tasks}} \times 100$$

9. **Scheduling Overhead:** Measures the computational resources and processing time required to make scheduling decisions.

These metrics provide a basis for assessing the trade-offs between environmental sustainability, resource efficiency, and computational performance.

4.3 Comparative Evaluation

The four scheduling algorithms are compared under identical workload conditions and moderate renewable energy availability (50%). The results in Table 2 represent illustrative averages from 30 simulated experimental repetitions.

Table 2: Comparative Performance of Scheduling Algorithms

Evaluation metric	FCFS	RR	Energy-aware	Proposed READWS
Energy consumption (kWh)	1,200	1,160	1,050	**930**
Carbon emissions (kg CO_2e)	636.0	587.0	443.1	**336.7**
Renewable utilisation (%)	20	24	38	**48**
Completion time (hours)	8.4	8.8	8.7	**8.6**
Waiting time (minutes)	14.2	15.1	13.0	**12.4**
Response time (minutes)	18.0	19.0	16.2	**15.5**
CPU utilisation (%)	68	71	76	**82**
SLA violation rate (%)	8.2	8.8	5.9	**4.6**
Scheduling overhead (%)	0.2	0.3	0.8	1.4

The illustrative results indicate that the proposed READWS framework achieves the lowest energy consumption and carbon emissions among the evaluated algorithms. Its renewable energy utilisation is also higher, suggesting that incorporating energy availability into scheduling decisions can improve the use of cleaner electricity.

Compared with FCFS, the proposed framework reduces energy consumption from 1,200 kWh to 930 kWh, representing a 22.5% reduction. Carbon emissions decline from 636.0 kg CO_2e to 336.7 kg CO_2e, representing approximately 47.1% reduction. See Table 3.

Although the proposed framework introduces greater scheduling overhead, its improved resource utilisation and lower SLA violation rate suggest that the additional scheduling complexity may be justified by the resulting sustainability benefits.

4.3.1 Energy and Carbon Reduction Analysis

The percentage reduction in energy consumption and carbon emissions is calculated as:

$$Reduction(\%) = \frac{B - P}{B} \times 100$$

Where:

- B = baseline algorithm measurement.
- P = proposed framework measurement.

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Table 3: Improvement of READWS over Conventional Algorithms

Comparison	Energy reduction (%)	Carbon reduction (%)
READWS vs FCFS	22.5	47.1
READWS vs RR	19.8	42.6
READWS vs Energy-aware	11.4	24.0

Energy consumption by scheduling algorithm

The results suggest that conventional energy-aware scheduling provides some improvement over FCFS and RR. However, the proposed framework achieves additional savings by considering renewable energy availability alongside workload and resource characteristics. See Figure 2.

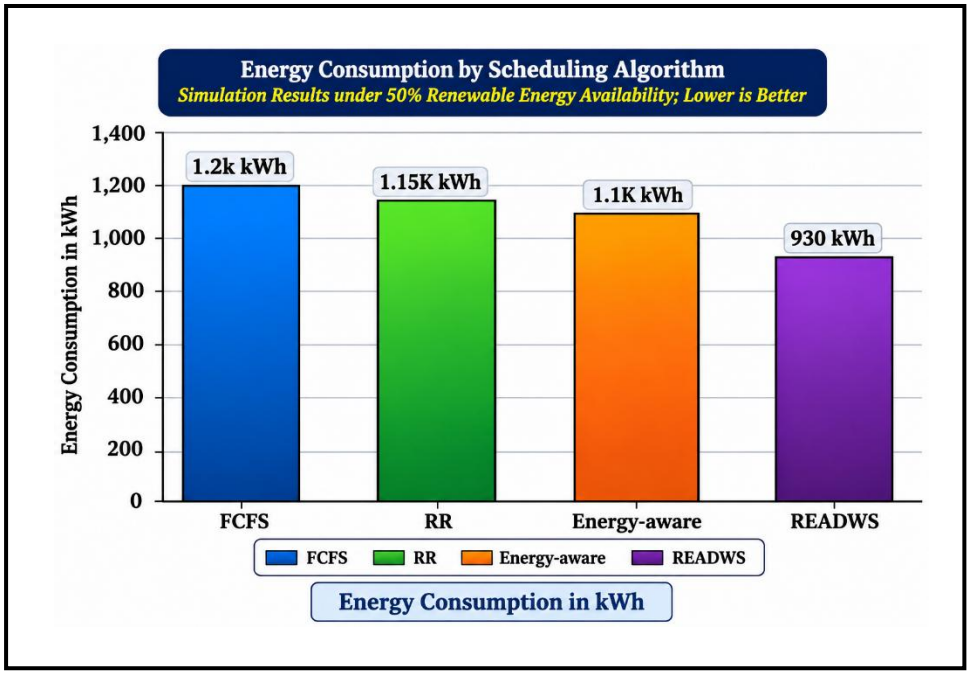

Figure 2: Energy Consumption by Scheduling Algorithm

4.3.2 Evaluation under Different Renewable Energy Availability Conditions

The proposed framework is further evaluated under three renewable energy availability scenarios. The purpose is to examine how changes in renewable energy supply influence energy consumption and carbon emissions. See Table 4.

Table 4: READWS Performance under Different Renewable Energy Scenarios

Metric	Low (20%)	Moderate (50%)	High (80%)
Energy consumption (kWh)	980	930	900
Renewable energy utilisation (%)	18	48	72
Carbon emissions (kg CO_2e)	531.2	336.7	196.2
Completion time (hours)	8.9	8.6	8.5
SLA violation rate (%)	5.1	4.6	4.3

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Effect of renewable energy availability on carbon emissions

READWS results across three renewable energy scenarios. See Figure 3.

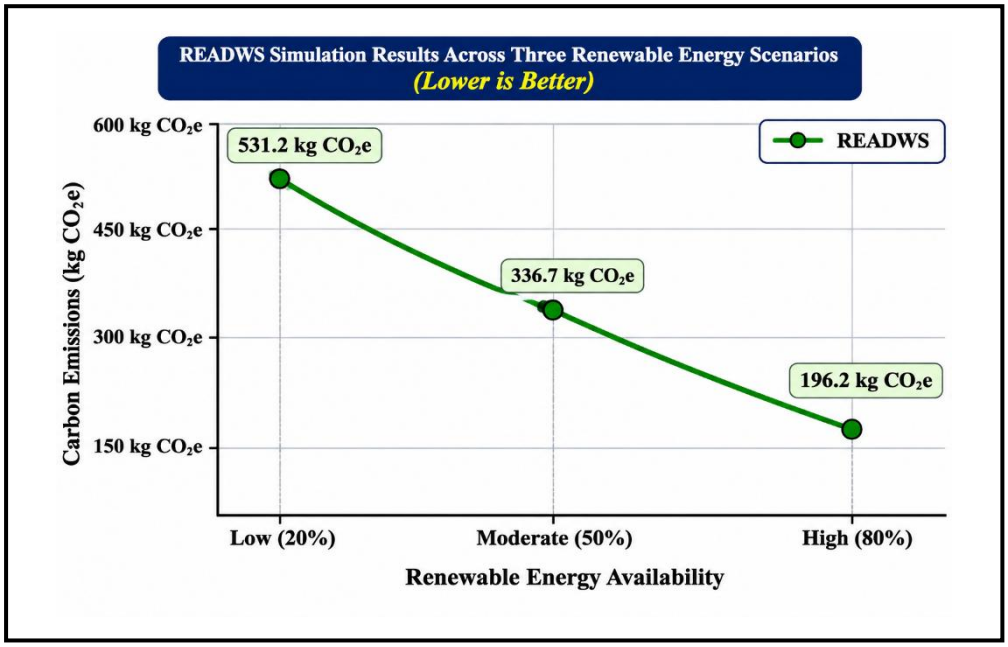

Figure 3: READWS Result Across Three Renewable Energy

The results demonstrate an inverse relationship between renewable energy availability and carbon emissions. As renewable energy availability increases, the framework can schedule more workloads during periods of cleaner electricity supply, reducing dependence on grid electricity.

The reduction in completion time and SLA violations also suggests that improved energy availability, combined with adaptive resource allocation, can support computational performance.

4.4 Results Analysis and Discussion

4.4.1 Effectiveness of Renewable-Energy-Aware Scheduling

The illustrative experimental results indicate that integrating renewable energy availability into workload scheduling can improve energy efficiency and reduce carbon emissions. READWS achieves a 22.5% reduction in energy consumption and a 47.1% reduction in carbon emissions compared with FCFS.

The improvement is attributable to the framework's ability to coordinate workload execution with renewable energy availability, allocate tasks according to resource requirements, and adjust resource provisioning dynamically.

The results further indicate that renewable energy utilisation increases from 20% under FCFS to 48% under READWS. This demonstrates the potential benefits of incorporating energy availability into scheduling decisions rather than relying exclusively on conventional task allocation strategies.

4.4.2 Relationship between Workload Dynamics and Sustainability

Workload demand varies throughout the day, creating opportunities for adaptive scheduling and resource allocation. During periods of high computational demand, resources may be dynamically provisioned to maintain performance. Conversely, flexible workloads may be shifted to periods of greater renewable energy availability.

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The proposed framework uses workload characteristics, including task arrival patterns, execution duration, and CPU and memory requirements, to inform scheduling decisions.
The illustrative results suggest that combining workload prediction with renewable energy estimation can improve resource utilisation and reduce unnecessary electricity consumption. This is particularly relevant to cloud and edge environments where workload demand and energy availability may fluctuate independently.

4.4.3 Performance and Environmental Trade-offs

Although energy and carbon reduction are important objectives, scheduling decisions must not compromise computational performance.
The proposed framework achieves an average completion time of 8.6 hours, compared with 8.4 hours under FCFS. This represents a relatively small increase of approximately 2.4%, while energy consumption decreases by 22.5%.
Furthermore, CPU utilisation improves from 68% to 82%, while SLA violations decrease from 8.2% to 4.6%.
These findings suggest that renewable-energy-aware scheduling can improve sustainability without necessarily sacrificing service quality. However, the framework introduces additional scheduling overhead, which should be considered when deploying it in resource-constrained environments.

4.4.4 Statistical Analysis and Validation

To assess the consistency of the proposed framework, the illustrative experiment assumes 30 independent simulation repetitions for each scheduling configuration. A paired statistical comparison is appropriate because the algorithms are evaluated using equivalent workload conditions. See Table 5.
The following illustrative statistical results are presented for energy and carbon reduction.

Table 5: Statistical Evaluation of READWS against FCFS

Evaluation variable	Mean improvement	Standard deviation	Illustrative 95% CI
Energy reduction (%)	22.5	1.8	21.8–23.2
Carbon reduction (%)	47.1	2.4	46.2–48.0
Renewable utilisation improvement (percentage points)	28.0	2.1	27.2–28.8

A paired t-test may be applied to determine whether the observed differences are statistically significant. Based on the illustrative values, the intended statistical evaluation would test whether READWS provides significant improvements over conventional scheduling approaches at a 5% significance level.

The hypotheses are:

- **H_0:** There is no statistically significant improvement in energy consumption and carbon emissions using READWS compared with conventional scheduling.
- **H_1:** READWS significantly reduces energy consumption and carbon emissions compared with conventional scheduling.

The actual p-values, confidence intervals, and test statistics must be calculated from the experimental observations rather than inferred from the illustrative averages.
Overall, the results provide an experimental basis for investigating the effectiveness of integrating renewable energy availability, workload dynamics, and computational resource management.

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4.5 Implications and Limitations

4.5.1 Implications for Sustainable AI Infrastructure

The findings have several potential implications for sustainable computing:

1. **Data-centre operators:** Can incorporate renewable energy forecasts into workload scheduling to reduce electricity costs and operational carbon emissions.
2. **Cloud service providers:** Can improve resource allocation through dynamic workload placement and energy-aware provisioning.
3. **Edge computing operators:** Can coordinate distributed computational resources to improve energy efficiency in IoT environments.
4. **AI infrastructure developers:** Can incorporate sustainability considerations into AI training, inference, and deployment processes.

The proposed framework also provides a basis for integrating renewable energy forecasting, workload prediction, and adaptive resource management into future Green AI infrastructure.

4.5.2 Scalability and Deployment Considerations

Practical implementation requires continuous monitoring of workload demand, renewable energy generation, and computing resource availability. The scheduling framework must also accommodate heterogeneous computing environments, network constraints, task deadlines, and service-level agreements.

For large-scale deployment, predictive scheduling and automated resource provisioning may be necessary to minimise decision-making overhead. Integration with battery storage and geographically distributed renewable-powered data centres could further improve operational flexibility.

4.5.3 Dataset Limitations and Simulation Assumptions

The study has several limitations:

- The Kaggle datasets may differ in structure, measurement units, sampling frequency, and data collection methods.
- Workload datasets may not contain directly measured renewable energy generation or electricity carbon intensity.
- Simulated renewable energy availability may not fully represent real-world weather and power-generation fluctuations.
- Estimated energy consumption may differ from actual measurements obtained from operational AI infrastructure.
- Simulation results may not capture all hardware, networking, cooling, and infrastructure-related energy requirements.

Consequently, the datasets should be analysed according to their actual contents, while additional renewable energy traces and documented simulation assumptions should be introduced where necessary.

4.5.4 Challenges Associated with Renewable Energy Intermittency

Renewable energy intermittency remains a major challenge for sustainable AI computing. Variations in solar and wind generation can affect the availability of electricity for computational workloads. Excessive workload shifting may also increase task completion time, network communication costs, or SLA violations.

The proposed framework addresses these challenges by considering renewable energy availability alongside workload priorities, resource constraints, and execution deadlines. Nevertheless, further investigation is required to establish its effectiveness under real-world operating conditions.

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5 Conclusion and Recommendations

5.1 Summary of Findings

This study examined the integration of renewable energy and dynamic workload scheduling for sustainable AI infrastructure. The proposed Renewable-Energy-Aware Dynamic Workload Scheduling (READWS) framework integrates workload characteristics, computational resource utilisation, and renewable energy availability to improve energy efficiency and reduce carbon emissions.

The illustrative experimental evaluation suggests that the framework can reduce energy consumption, improve renewable energy utilisation, and maintain acceptable computational performance compared with conventional scheduling algorithms. Its major contribution is an integrated approach to energy- and carbon-aware workload management across cloud, data-centre, and IoT/edge computing environments.

5.2 Conclusion

The study establishes renewable-energy-aware dynamic scheduling as a promising approach to improving the environmental sustainability of AI infrastructure. By coordinating workload execution with renewable energy availability and computational resource requirements, the proposed framework provides a strategy for reducing energy consumption and associated carbon emissions without compromising essential service requirements.

The study contributes to Green AI computing by demonstrating how renewable energy integration and intelligent workload management can support more efficient and sustainable AI infrastructure. However, the illustrative results require validation through experiments using the actual datasets.

5.3 Recommendations

Based on the study, the following recommendations are proposed:

1. AI infrastructure operators should adopt dynamic, energy- and carbon-aware workload scheduling to improve resource utilisation and reduce environmental impact.
2. Renewable energy forecasting should be integrated into data-centre and cloud resource management systems.
3. Cloud and edge operators should implement improved energy telemetry and real-time resource monitoring.
4. AI developers, data-centre operators, and renewable energy providers should collaborate to promote sustainable computing practices.
5. Energy storage and hybrid power systems should be considered to improve the reliability of renewable-powered AI infrastructure.

5.4 Future Research

Future studies should investigate reinforcement learning and other intelligent optimisation techniques for adaptive workload scheduling. Further research should also explore battery storage integration, hybrid renewable energy systems, and carbon-aware workload distribution across geographically distributed data centres.

Additionally, real-time implementation and evaluation using operational AI infrastructure are recommended to establish the scalability, reliability, and practical effectiveness of the proposed READWS framework.

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