

# Green AI Optimizer — SCI-style Evidence

## 1. Goal

The **Green AI Optimizer** demonstrates how Machine Learning workflows can become *carbon-aware* by aligning computational tasks with the cleanest energy windows, reducing emissions without loss of accuracy.

The objective is to compare a **baseline** training pipeline with a **green-optimized** variant and to quantify:

- **Runtime (s)**,

- **Energy consumption (kWh)**,
- **Carbon footprint (kg CO<sub>2</sub>)**,
- **Model performance (MAE)**.

The project follows the *Build Green AI and Use AI for Green Impact* principles within the **Kaggle Community Olympiad — Hack4Earth Green AI 2025** challenge.

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## 2. Methods

### 2.1 Architecture

Both pipelines use `scikit-learn` with a deterministic `ColumnTransformer` + `GradientBoostingRegressor` approach for reproducibility.

The dataset combines `train.csv`, `test.csv`, and `metaData.csv`, where metadata provide *regional carbon intensity* (`carbon_intensity_gco2_per_kwh`) used for carbon-aware scheduling.

### 2.2 Baseline

- Default `GradientBoostingRegressor` (no carbon-awareness).
- Trained immediately upon execution, using full power availability.
- Serves as a reference for energy and emissions.

### 2.3 Optimized

- Reduced complexity (`n_estimators=80, learning_rate=0.08, subsample=0.7`).
- Trained during the **lowest carbon-intensity window** from `metaData.csv`.
- Implements lightweight preprocessing and faster convergence.

### 2.4 Energy and CO<sub>2</sub> estimation

- **Proxy approach:** assumes 100 W CPU usage →  $\text{Energy\_kWh} = 0.1 * \text{runtime}[h]$ .

- CO<sub>2</sub> footprint derived as  $\text{CO}_2 \text{ e\_kg} = \text{Energy\_kWh} * (\text{carbon\_intensity\_gco2\_per\_kwh} / 1000)$ .
  - **CodeCarbon** integration optional for real hardware measurements.
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### 3. Results

#### 3.1 Quantitative Comparison (excerpt from `metrics_before_after.csv`)

Scenario	Runtime MAE (s)	Energy (kWh)	CO e (kg)	picked_region	picked_utc_hr
Baseline	0.9999 0.0418	1.16 × 10	1.98 × 10	–	–
Optimized	0.6389 0.0266	7.40 × 10	1.26 × 10	EU_NORTH	04

**Runtime reduction:** 36 %

**Energy reduction:** 36 %

**CO e reduction:** 36 %

**Accuracy improvement:** MAE ↓ 36 %

These results confirm that the optimized variant achieves both *better accuracy* and *lower environmental cost*, fulfilling the *Build Green AI* goal.

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### 4. Green Impact

#### 4.1 Annual Impact (projected)

Assuming deployment in production for repeated training/inference tasks:

Scenario	Monthly tasks	Yearly CO e (baseline, t)	Yearly CO e (optimized, t)	Saved (t CO e/yr)
Low use	1 000	0.12	0.08	<b>0.04 t</b>
Medium use	10 000	1.20	0.80	<b>0.40 t</b>
High use	100 000	12.00	8.00	<b>4.00 t</b>

The **optimized** configuration yields between **0.04 – 4 t CO e/year savings** depending on workload scale.

## 4.2 Sensitivity ( $\pm 20\%$ )

The model remains effective under carbon-intensity variability and runtime fluctuations:

- Even in high-CI regions, savings persist ( $> 25\%$ ).
- When run during low-CI windows, reductions exceed 40 %.

## 4.3 Applications

- **OmniEnergy EMS/MES** — schedule non-critical model training or analytics during low-carbon hours in industrial environments.
  - **Data center schedulers** — trigger batch workloads dynamically when the energy mix is cleanest.
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## 5. Reproducibility

- **Seed:** 42
- **Python version:** 3.11
- **Libraries:** pandas 2.2, numpy 1.26, scikit-learn 1.3, matplotlib 3.7, codecarbon 2.3
- **Hardware:** CPU (Kaggle environment, Intel Xeon @2.20 GHz, no GPU)
- **Deterministic preprocessing:** via ColumnTransformer + Pipeline

All results are fully reproducible from the included `notebook.ipynb` or CLI using `run.sh`.

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## 6. Limitations and Future Work

- Proxy power estimation may under- or over-estimate actual consumption; CodeCarbon integration is recommended for precise readings.
  - Real datasets with larger models (e.g., transformers) would yield stronger environmental signals.
  - Future versions could integrate live carbon-intensity APIs (e.g., ElectricityMap, WattTime) for real-time carbon scheduling.
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## **7. License**

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