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AI-Enhanced Life Cycle Assessment of Circular Energy–Waste Systems in Sustainable Built Environments

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Abstract: This study develops a compact, reproducible workflow that links life cycle assessment (LCA) with simple, interpretable machine-learning to assess carbon outcomes of distributed energy resources (DER), variable renewable energy (VRE) and circular waste options at building/precinct scale. Scope is limited to carbon-related flows (energy, waste, emission factors). As an illustration, the University of Queensland's Advanced Engineering Building (AEB) is used with publicly available information only. The LCA core runs in Brightway2; a multivariate linear regression explains how a small set of drivers (VRE share, storage sizing, waste diversion, emission-factor choice) shape annual carbon intensity. Outputs include carbon intensity, contribution analysis, ranked drivers and uncertainty ranges. Prior work suggests two design anchors: (i) LCSA benefits from integrating methods and systems thinking rather than treating tools in isolation (Onat et al., 2017); and (ii) AI–LCA can reduce inventory burden if models remain transparent and data-fit is checked (de Jesus et al., 2021). Results suggest that diversion rates and emission-factor choices have stronger influence on the footprint than small variations in storage. Overall, the workflow highlights dominant drivers and provides a transparent basis for early building-scale decisions.

Keywords: Distributed energy resources, variable renewable energy, circular waste, life cycle assessment

1. INTRODUCTION

Decarbonising buildings needs evidence that links life-cycle metrics with day-to-day operational choices. Onat et al. (2017) review Life Cycle Sustainability Assessment (LCSA) and argue that practical application "requires integration of various methods, tools, and disciplines," which motivates coupling LCA with simple analytics and systems views rather than using either in isolation. In parallel, a structured AI–LCA review finds that machine-learning can support data handling and build predictive surrogates, but warns about data suitability and over/under-fitting; interpretability is stressed (de Jesus et al., 2021).

The Advanced Engineering Building (AEB) at The University of Queensland provides a suitable public-data case: the UQ Solar facility page documents a 95.75 kWp rooftop PV system and mixed-mode air-conditioning, enabling DER and VRE scenarios without proprietary data (The University of Queensland, n.d.). National Greenhouse Accounts Factors (DCCEEW, 2024) are used for electricity, fuel, and waste emission factors to align with current Australian practice. We emphasise transparent inventories, interpretable regression, and explicit uncertainty outputs (Ma et al., 2022).

2. METHODOLOGY AND RESULTS

Readiness framing. We used a readiness lens, inspired by maturity-model thinking, simply to check suitability rather than to rank stages.

Data and modelling. The functional unit is one year of AEB operation. The system boundary includes on-site PV and storage (if present), grid imports, any minor fossil back-up, and waste handling (recycling/composting, biodigestion, waste-to-energy where relevant). Inventories are versioned with source–year–region tags, and emission factors follow the National Greenhouse Accounts (NGA) Factors 2024 (DCCEEW, 2024). LCA is implemented in Python using Brightway2 (Mutel, 2017). Annual carbon intensity (kg CO_2-e $m^{-2}\cdot yr^{-1}$) is explained with a multivariate linear regression; global sensitivity ranks the drivers, and Monte Carlo analysis provides 5–95 % ranges.

How the table is used. Table 1 lists the software stack (LCA engines, databases, statistics, and plotting) with each tool's role. It acts as a methods checklist for reproducibility and reviewer audit, not as a results table.

Table 1. Open tools for AI-augmented LCA (used and/or cross-checked)

Category	Tool	Purpose	Notes
LCA platform	Brightway2 (Python)	Core LCI/LCIA; Monte Carlo	Open-source; reproducible scripts
LCA platform	openLCA	GUI build; cross-checks; EPD imports	Open-source
Databases	AusLCI / ecoinvent	Electricity mixes, materials, waste routes	Public/open where possible; versioned
Emission factors	NGA Factors (Australia, 2024)	Grid/fuel/waste factors	Official guidance
AI/ML	scikit-learn	Linear regression; permutation importance	Interpretable baseline
Sensitivity	SALib	Global sensitivity (Sobol/Morris)	Reproducible
Statistics	statsmodels	OLS diagnostics; confidence intervals	Model checks
Uncertainty	NumPy / SciPy	Sampling; distribution fitting	Monte Carlo runs
Visualisation	Matplotlib / dashboard	Plots; what-if sliders	Low barrier for facility teams

3. CONCLUSIONS

This workflow links process-based LCA with a simple, interpretable regression to assess DER/VRE and circular-waste options at building scale using public data. It makes key drivers visible, shows uncertainty clearly, and leaves an audit trail that others can repeat.

First, inventories should gradually be tightened with metered and site-specific factors to reduce reliance on generic databases. Second, circular options such as biodigestion, composting and PV-storage tuning should be prioritised as "no-regrets" measures that are both low-cost and easy to communicate. Linking these indicators moves the exercise beyond research and turns it into a working strategy: universities and councils could use it to weigh different options, make their assumptions explicit, and refresh results as new evidence appears (Onat et al., 2017).

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REFERENCES

de Jesus JO, de Oliveira-Esquerre K and Medeiros DL (2021) Integration of artificial intelligence and life cycle assessment methods. IOP Conference Series: Materials Science and Engineering 1196, 012028

Department of Climate Change, Energy, the Environment and Water (DCCEEW) (2024) National Greenhouse Accounts Factors 2024. Australian Government, Canberra. Available at: https://www.dcceew.gov.au/sites/default/files/documents/national-greenhouse-account-factors-2024.pdf (accessed 17 August 2025)

Ma W, Hao J, Zhang C, Guo F and Di Sarno L (2022) System dynamics–life cycle assessment causal loop model for evaluating the carbon emissions of building refurbishment construction and demolition waste. Waste and Biomass Valorization 13(9), 4099–4113

Mutel C (2017) Brightway: An open-source framework for life cycle assessment. Journal of Open-Source Software 2(12), 236

Onat NC, Kucukvar M, Halog A and Cloutier S (2017) Systems thinking for life cycle sustainability assessment: A review of recent developments, applications, and future perspectives. Sustainability 9(5), 706

The University of Queensland (n.d.) Advanced Engineering Building – Solar. Available at: https://solar-energy.uq.edu.au/facilities/st-lucia/advanced-engineering-building (accessed 17 August 2025)

