ORIGINAL RESEARCH **Open access**

Sustainable Artificial Intelligence in Energy Systems: Computational Efficiency, Carbon-Aware Algorithms, and Life-Cycle Responsibility

James O'Leary[1*], Aisling Dunne[1], Sean O'Brien[2]

Abstract

AI is widely used to improve energy system efficiency, but its own growing energy consumption and environmental footprint are raising concerns. The sustainability of AI in the energy sector must be addressed as an integral part of its governance. Current frameworks for AI in energy focus on optimising the energy system itself, ignoring the direct and embodied environmental impacts of the AI systems deployed. A holistic sustainability framework is lacking. This article develops a framework for sustainable AI in energy systems, built around three pillars: computational efficiency, carbon-aware algorithms, and life-cycle responsibility. The framework is constructed through conceptual synthesis of green AI research, carbon-aware computing, life-cycle assessment, and energy policy. No empirical analyses are performed. The framework specifies strategies for minimising AI's energy use, aligning its computation with low-carbon energy availability, and managing the full life-cycle environmental impact of AI hardware and software. Two tables summarise the pillars and their interactions. Integrating sustainability into the core design of AI for energy systems can ensure that AI contributes positively to the energy transition, avoiding a rebound effect where AI's own footprint undermines its benefits.

Keywords Autonomous energy systems, Sustainable AI, Green AI, Carbon-aware algorithms, Life-cycle responsibility, Computational efficiency

*Correspondence:
James O'Leary
james.oleary@tcd.ie
[1] Department of Artificial Intelligence for Electricity Market Analytics, School of Engineering, Trinity College Dublin, Dublin, Ireland
[2] Department of Intelligent Power Systems and Machine Learning, Faculty of Engineering, University College Dublin, Dublin, Ireland

Introduction

Artificial intelligence increasingly occupies a dual position in energy systems: it is promoted as a tool for reducing waste, improving forecasting, coordinating demand response, and supporting renewable integration, while also becoming a resource-consuming digital infrastructure in its own right. Green AI scholarship has shown that model development can impose substantial computational burdens, making efficiency a central design concern rather than a secondary technical preference [1]. The environmental implications of AI are therefore not external to energy governance, because AI models used for optimisation may themselves contribute to electricity demand, hardware turnover, and data-centre expansion [2]. Sustainable AI in energy systems must begin from this duality, recognising that a technology designed to solve energy problems can also reproduce or intensify them.

AI applications in smart grids, renewable energy forecasting, building energy prediction, and power system planning are often justified by their expected contribution to efficiency, reliability, and flexibility. Reviews of machine learning for

This is an open access article distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License (CC BY-NC-SA 4.0), which permits non-commercial use, distribution, reproduction, and adaptation in any medium or format, provided that appropriate credit is given to the original author(s) and source, a link to the license is provided, and any changes made are indicated. Adapted material must be distributed under the same license.

© 2025 The Author(s). | Published by Institute of Smart Energy Systems Press

sustainable energy systems demonstrate that AI can support low-carbon system operation, but this does not automatically mean that the AI system itself is environmentally responsible [3]. The growing literature on AI for renewable energy and smart grids likewise tends to focus on operational gains, while the energy and material cost of computation remains less integrated into governance models [4]. This gap creates the risk that energy-sector AI may be evaluated only by downstream benefits, without accounting for the upstream and operational footprint required to produce those benefits.

Sustainable AI should therefore be treated as a design principle embedded across model development, deployment, procurement, and governance. The first pillar, computational efficiency, asks whether an AI task can be accomplished with fewer parameters, less training, leaner inference, or more efficient architectures, reflecting the Green AI argument that resource use should be reported and minimised alongside performance [1]. The second pillar, carbon-aware algorithms, extends this logic by asking whether AI workloads could be aligned with low-carbon electricity availability rather than treated as temporally and spatially neutral computational tasks [5]. The third pillar, life-cycle responsibility, requires attention to embodied emissions, hardware manufacture, equipment replacement, and end-of-life management, which broader ICT footprint studies identify as essential for credible environmental accounting [6].

This article develops a conceptual framework for sustainable AI in energy systems centred on computational efficiency, carbon-aware algorithms, and life-cycle responsibility. It draws on sustainable AI theory, green computing, carbon-aware data-centre research, life-cycle assessment, and AI-for-energy scholarship to specify how environmental responsibility can be internalised into AI design and governance [7]. The framework is not an empirical measurement model and does not report performance, energy, or carbon results; instead, it provides a normative and analytical structure for guiding future system design. The article proceeds from background and conceptual foundations to the three-pillar framework, then examines efficiency design, carbon-aware scheduling, life-cycle responsibility, governance, evaluation, limitations, and conclusions.

Background

AI's growing energy footprint

AI's environmental footprint has become increasingly visible because modern model development may require energy-intensive training, repeated experimentation, large-scale inference, and specialised computing infrastructure. The critique of Green AI argues that accuracy-centred research cultures can reward larger and more computationally expensive models even when smaller alternatives might deliver sufficient performance for practical tasks [1]. Work estimating the carbon footprint of large models has further highlighted that AI's environmental impact includes not only one-time training but also hardware use, deployment context, and energy source characteristics [8]. In energy systems, these concerns are especially important because AI is often justified by sustainability goals, making its own footprint a matter of environmental integrity.

Green AI and sustainable computing

Green AI and sustainable computing seek to reduce the resource requirements of computation while preserving useful functionality. Sustainable AI has been framed as involving both AI for sustainability and the sustainability of AI itself, a distinction that is crucial for energy systems because optimisation benefits should not be separated from computational costs [7]. Methods such as model compression, efficient architecture selection, energy-aware training, and transparent reporting can help shift AI development away from purely scale-driven assumptions [1]. Sustainable computing research also shows that digital technologies require systemic assessment, since efficiency gains can be offset by expanding demand, rebound effects, and insufficient governance [6].

Carbon-aware computing

© 2025 The Author(s). | Published by Institute of Smart Energy Systems Press

Carbon-aware computing reframes computation as a flexible demand that can, in some contexts, be shifted across time or location to reduce reliance on high-carbon electricity. Data-centre research has shown that carbon-aware scheduling can align workloads with lower-carbon grid conditions, making the timing and geography of computation central to environmental performance [5]. Renewable-aware load balancing similarly suggests that digital services can be routed or scheduled according to renewable electricity availability, although this requires coordination among computational demand, network constraints, and service requirements [9]. For AI in energy systems, carbon awareness is not only a data-centre strategy but also a principle for designing algorithms that recognise the carbon consequences of their own execution.

Life-cycle thinking in digital technologies

Life-cycle thinking expands environmental assessment beyond electricity consumed during computation to include embodied carbon, equipment production, data-centre infrastructure, maintenance, and disposal. ICT footprint research demonstrates that digital sustainability cannot be understood through operational energy alone, because device manufacture, infrastructure growth, and media or computing demand all contribute to long-term environmental impact [10]. Studies of global ICT and entertainment-sector footprints also show that energy and carbon responsibility must consider both use-phase electricity and the material base of digital systems [11]. For AI in energy systems, life-cycle responsibility means that GPUs, accelerators, servers, cooling systems, and replacement cycles become part of the sustainability evaluation. **Figure 1** illustrates how life-cycle thinking expands AI sustainability assessment beyond computational electricity use to include embodied carbon, hardware production, data-centre infrastructure, maintenance, cooling, replacement cycles, and end-of-life disposal.

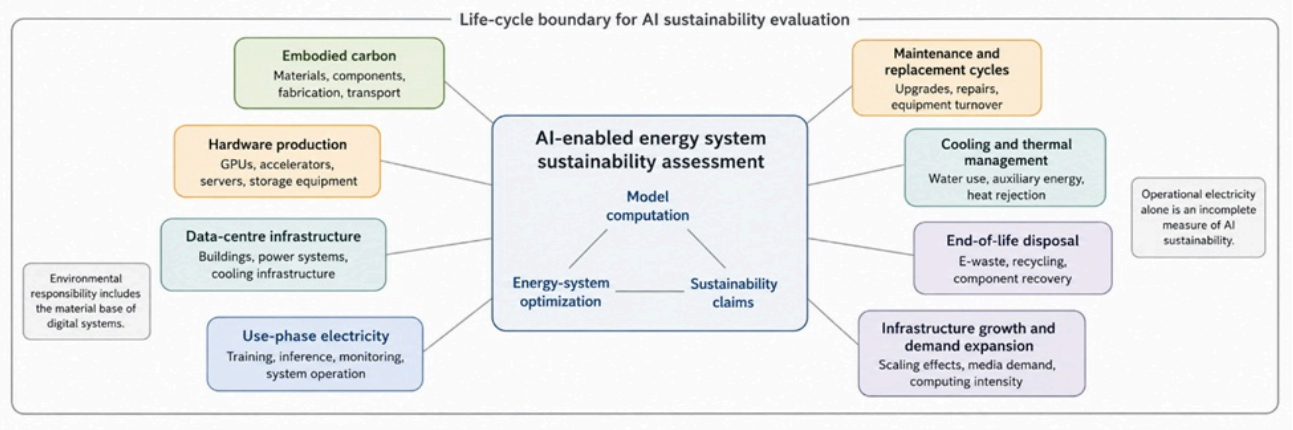


Figure 1. Life-Cycle Responsibility in AI-Enabled Energy Systems

Regulatory and standardization landscape

The regulatory and standardisation landscape for sustainable AI remains less mature than the technical literature on AI optimisation and energy-system applications. Research on artificial intelligence, systemic risk, and sustainability argues that governance must address indirect, systemic, and cross-sector effects rather than treating AI as a purely technical instrument [12]. Sustainable AI ethics scholarship further suggests that environmental responsibility should be embedded into institutional decision-making, procurement, and accountability structures rather than left to voluntary reporting alone [7]. In energy systems, this implies that utilities, technology vendors, regulators, and system operators should develop governance expectations for AI footprint disclosure, carbon-aware deployment, and life-cycle accountability.

Conceptual Foundation

Defining sustainable AI for energy systems

© 2025 The Author(s). | Published by Institute of Smart Energy Systems Press

Sustainable AI for energy systems can be defined as the design, deployment, and governance of AI systems that minimise their own environmental footprint while enhancing the sustainability, reliability, and justice of the energy system they serve. This definition extends the distinction between AI for sustainability and the sustainability of AI by insisting that both dimensions must be assessed together [7]. Machine learning may support renewable integration, demand-side flexibility, grid optimisation, and energy planning, but these benefits should be evaluated against the resources required to develop and operate the models [3]. Sustainable AI therefore requires normative and technical commitment to ensuring that AI's net contribution to the energy transition remains environmentally credible.

The three pillars

The proposed framework rests on three interdependent pillars: computational efficiency, carbon-aware algorithms, and life-cycle responsibility. Computational efficiency draws from Green AI by prioritising models that can be trained and deployed with lower resource demands while remaining adequate for the intended energy-system function [1]. Carbon-aware algorithms build on data-centre and workload-shifting research by aligning computation with low-carbon electricity availability where latency, reliability, and operational constraints permit [5]. Life-cycle responsibility incorporates ICT and AI life-cycle perspectives, requiring attention to embodied emissions, hardware longevity, supply chains, and end-of-life impacts [13].

Figure 2 presents the Archetype AI Sustainability Life-Cycle Framework, showing how computational efficiency, carbon-aware algorithms, and life-cycle responsibility govern AI across the full design-to-retirement pathway.

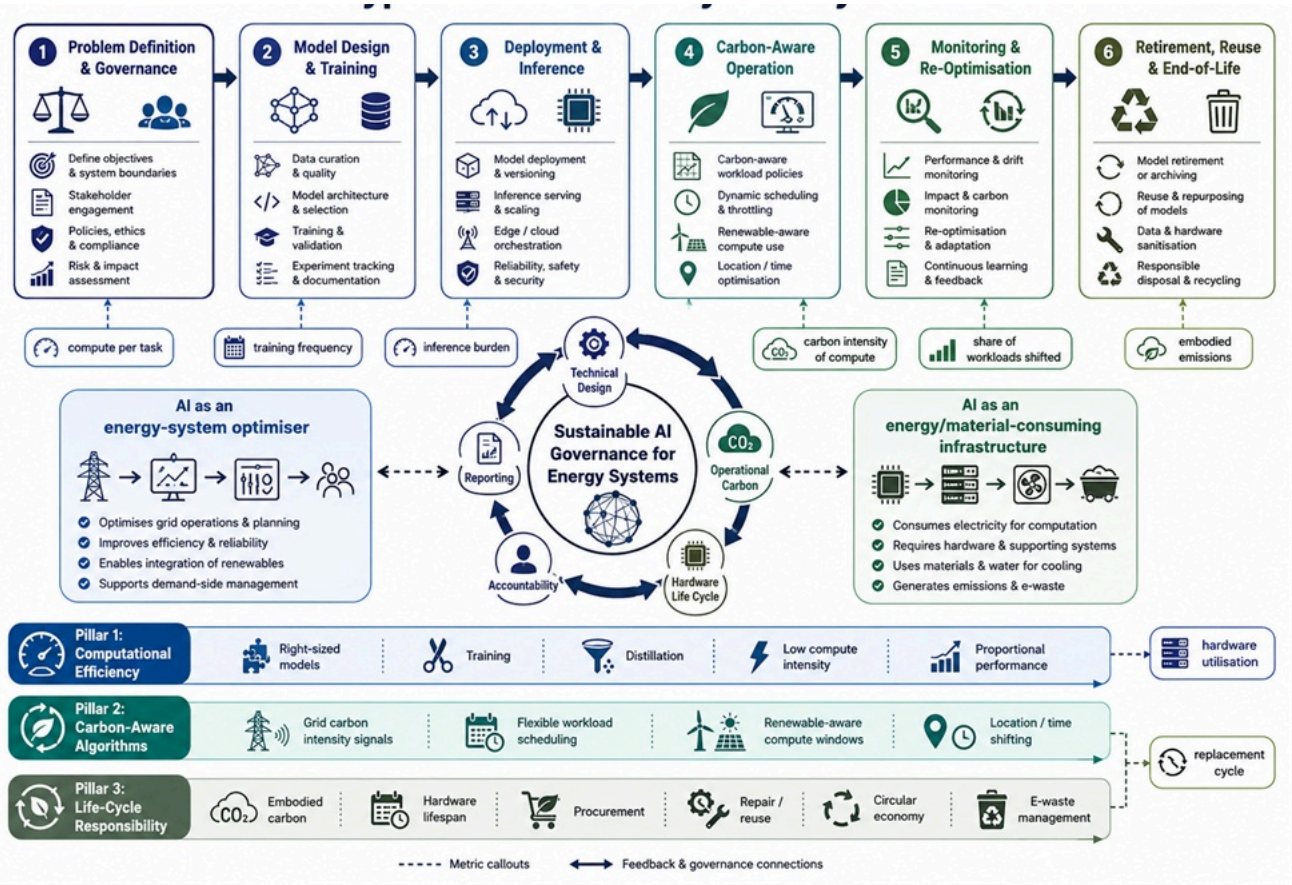


Figure 2. Archetype AI Sustainability Life-Cycle Framework

Integrating AI footprint into energy system modelling

© 2025 The Author(s). | Published by Institute of Smart Energy Systems Press

AI's energy demand should be modelled as part of the energy system it serves rather than treated as an invisible external cost. Research on AI for sustainable energy systems shows that machine learning can become embedded in forecasting, dispatch, control, and planning workflows, which means its computational requirements may become routine components of energy-system operation [3]. If AI workloads grow alongside smart-grid, building, prosumer, and renewable-energy applications, their cumulative demand could influence the very systems they are meant to optimise [14]. A sustainable framework must therefore conceptualise AI computation as a controllable and governable energy load, subject to efficiency requirements, carbon-aware scheduling, and life-cycle accounting.

Framework Components: Three Pillars

Computational efficiency

Computational efficiency focuses on reducing the resources required to train, validate, update, and deploy AI models in energy contexts. Green AI research argues that efficiency should be valued alongside predictive or optimisation performance, because marginal performance improvements may require disproportionate computational expansion [1]. In energy-system applications, efficient model design can include pruning, distillation, sparse modelling, feature discipline, transfer learning, and selecting the least complex model that can support the operational decision at stake [15]. This pillar does not imply that simple models are always preferable, but it requires that computational scale be justified by decision value, reliability needs, and sustainability consequences.

Carbon-aware algorithms

Carbon-aware algorithms seek to minimise environmental impact by aligning AI computation with low-carbon electricity availability across time and location. Data-centre carbon-aware computing shows that flexible workloads may be scheduled when grid carbon intensity is lower, while geographically distributed computing can route tasks toward cleaner electricity where infrastructure and governance allow [5]. In energy systems, this logic could apply to model retraining, scenario generation, non-urgent analytics, and other flexible computational tasks, while safety-critical real-time functions may require stricter latency and reliability constraints [9]. Carbon awareness therefore requires algorithmic scheduling rules that distinguish flexible from non-flexible AI workloads and treat carbon intensity as a governance-relevant signal.

Life-cycle responsibility

Life-cycle responsibility broadens sustainable AI beyond operational electricity use to include hardware production, data-centre infrastructure, equipment replacement, cooling, maintenance, and disposal. Life-cycle assessment of AI solutions has emphasised that environmental impacts can be hidden when attention is limited to model execution rather than the full socio-technical system supporting AI [13]. ICT emissions studies similarly show that embodied and infrastructure-related impacts must be considered when assessing the sustainability of digital systems [10]. In energy systems, life-cycle responsibility should be addressed through embodied carbon accounting, hardware longevity, repairability, reuse, procurement standards, and circular economy principles for AI infrastructure. **Table 1** summarises the proposed sustainable AI framework by outlining its three core pillars, the principal implementation strategies associated with each pillar, the metrics that can be used to evaluate performance, and the broader governance implications for responsible AI deployment in energy systems.

Table 1. Sustainable AI Framework: Pillars, Strategies, Metrics, and Governance Implications

Pillar	Core Strategies	Key Metrics	Governance Implications
Computational Efficiency	Prioritise right-sized models, pruning, distillation, efficient architectures, disciplined feature selection, reuse of	Compute intensity per task, training frequency, inference burden, model complexity relative to decision value, and	Requires procurement rules and model approval processes that ask whether computational scale is justified by operational need rather

© 2025 The Author(s). | Published by Institute of Smart Energy Systems Press

	trained components, and minimisation of unnecessary retraining.	efficiency-performance balance.	than prestige, novelty, or marginal accuracy gains.
Carbon-Aware Algorithms	Schedule flexible AI workloads during low-carbon electricity periods, route non-urgent computation to cleaner locations, and classify workloads by latency and reliability constraints.	Carbon intensity of compute windows, share of flexible workloads shifted, responsiveness to grid signals, and compatibility with reliability requirements.	Requires access to trusted carbon-intensity signals, operational policies for workload flexibility, and safeguards ensuring that carbon optimisation does not undermine critical energy-system functions.
Life-Cycle Responsibility	Account for embodied carbon, extend hardware lifespan, favour repair and reuse, manage end-of-life impacts, and evaluate software decisions that accelerate hardware turnover.	Embodied emissions, hardware utilisation, replacement cycles, reuse potential, end-of-life pathway, and full life-cycle environmental burden.	Requires vendor disclosure, circular procurement, infrastructure auditing, and accountability mechanisms that connect AI deployment decisions to material and supply-chain consequences.

Computational Efficiency and Green AI Design

Model optimisation techniques

Model optimisation techniques can reduce computational demand by aligning model complexity with the decision problem rather than assuming that larger models are inherently preferable. Green AI scholarship supports this shift by criticising research cultures that reward computational scale without adequately reporting or justifying resource consumption [1]. In energy applications, model compression, pruning, knowledge distillation, efficient neural architectures, and transfer learning could reduce the need for repeated high-cost training while preserving adequate decision support [15]. Such techniques should be designed to fit the operational context, because the sustainability value of efficiency depends on whether the resulting model remains reliable, interpretable, and useful for energy-system decisions.

Efficiency metrics and benchmarks

Efficiency metrics and benchmarks are needed so that sustainable AI can be evaluated systematically rather than treated as a rhetorical commitment. The Green AI perspective argues that computational cost should be reported alongside model performance, making efficiency visible to researchers, developers, and institutions [1]. For energy systems, appropriate benchmarks could include compute required per forecast, retraining burden per operational cycle, inference cost per decision, and the relationship between model complexity and practical decision value, without reducing sustainability to a single indicator [3]. These benchmarks should be embedded into governance processes so that AI systems are compared not only by predictive quality but also by their environmental and operational proportionality.

Balancing efficiency and performance

Balancing efficiency and performance requires careful judgement because the most computationally efficient model may not always be adequate for high-stakes energy-system functions. Reviews of AI in smart grids and power system operation show that reliability, control quality, and decision timeliness remain central requirements, especially where AI supports critical infrastructure [14]. Sustainable AI should therefore avoid a simplistic trade-off in which environmental efficiency is pursued by weakening operational safety, but it should also reject the opposite assumption that maximum computational scale is justified by any performance improvement [4]. The framework treats efficiency as a constraint on

© 2025 The Author(s). | Published by Institute of Smart Energy Systems Press

responsible design: models should be no more complex than necessary for their validated purpose, and any additional computational burden should be justified through clear operational and sustainability reasoning.

Carbon-Aware Algorithms and Temporal Flexibility

Leveraging real-time carbon intensity signals

Carbon-aware AI requires access to reliable signals about the carbon intensity of electricity used for computation, because the same AI workload can have different environmental implications depending on when and where it runs. Carbon-aware data-centre research shows that computing tasks can be coordinated with grid conditions when workload flexibility and operational constraints are explicitly recognised [5]. In energy systems, this principle could be extended to AI model retraining, forecasting updates, and non-urgent optimisation routines that do not require immediate execution. Such designs would be expected to make AI computation more responsive to the energy transition, rather than allowing AI demand to remain detached from the carbon profile of the grid it depends on.

Workload shifting and scheduling

Workload shifting and scheduling can be conceptualised as a governance mechanism as much as a technical optimisation strategy. Renewable-aware load balancing demonstrates that digital workloads may be distributed across locations or time periods according to renewable electricity availability, but this requires attention to service quality, infrastructure capacity, and operational feasibility [9]. For AI in energy systems, flexible training jobs, batch analytics, scenario generation, and model evaluation tasks could be scheduled for lower-carbon periods, while critical grid-control functions would require stronger reliability protections. This distinction matters because sustainable AI should be designed to minimise avoidable carbon impact without compromising the safety and continuity of essential energy operations.

Carbon-aware control and decision-making

Carbon-aware decision-making becomes more complex when AI is not merely consuming electricity but actively controlling energy assets, markets, or infrastructure. Machine learning for sustainable energy systems already supports forecasting, optimisation, demand response, and operational planning, which means AI decisions may influence both system emissions and the timing of electricity demand [3]. The broader literature on AI for climate mitigation suggests that AI can support decarbonisation, but only if its design is aligned with climate objectives rather than narrow technical efficiency alone [16]. **Table 2** illustrates how the three pillars can reinforce one another while also creating tensions that require explicit governance. **Table 2** demonstrates that the three sustainability pillars are deeply interconnected, generating both reinforcing synergies and practical tensions that require coordinated governance to balance computational efficiency, operational decarbonisation, and long-term life-cycle responsibility in AI-enabled energy systems.

Table 2. Synergies and Tensions between the Three Sustainability Pillars

Primary Pillar	Interaction with Computational Efficiency	Interaction with Carbon-Aware Algorithms	Interaction with Life-Cycle Responsibility
Computational Efficiency	Reinforces proportional model design by reducing unnecessary training, inference, and retraining burdens.	Supports carbon-aware scheduling by making workloads smaller and easier to shift, but excessive compression may reduce flexibility if models require frequent recalibration.	Extends hardware lifespan by reducing computational pressure, but efficiency-driven upgrades may unintentionally accelerate hardware replacement.

© 2025 The Author(s). | Published by Institute of Smart Energy Systems Press

Carbon-Aware Algorithms	Encourages efficient use of flexible compute windows, but carbon-optimised scheduling may require additional monitoring and orchestration overhead.	Reinforces temporal and spatial alignment between AI workloads and low-carbon electricity availability.	Can reduce operational emissions, but may increase infrastructure complexity if spatial routing depends on additional data-centre capacity.
Life-Cycle Responsibility	Encourages right-sized hardware and software longevity, but older hardware may be less energy efficient for some AI tasks.	Provides a check against carbon-aware strategies that reduce operational emissions while increasing embodied impacts through new infrastructure.	Reinforces full-system accountability by connecting procurement, operation, reuse, and end-of-life governance.

Market and regulatory enablers

Carbon-aware AI would require market and regulatory enablers that make low-carbon computation practical, verifiable, and institutionally valued. Energy transition research increasingly emphasises that AI must be integrated into broader governance and planning contexts rather than treated as a neutral optimisation tool [17]. Electricity markets, tariffs, procurement rules, and reporting requirements could create incentives for utilities, data-centre operators, and AI vendors to shift flexible workloads toward lower-carbon electricity availability. However, such incentives should be designed carefully, because carbon-aware scheduling in critical infrastructure must remain subordinate to reliability, equity, and public-interest obligations.

Life-Cycle Responsibility: Beyond Operational Carbon

Embodied carbon in AI hardware

Life-cycle responsibility requires attention to the embodied carbon and material impacts of AI hardware, including accelerators, servers, networking equipment, cooling infrastructure, and data-centre construction. The carbon impact of AI is not limited to electricity consumed during model training or inference, because hardware production and infrastructure expansion can create significant environmental burdens before computation begins [2]. Research on data-centre sustainability similarly argues that sustainable computing must revisit hardware, infrastructure, energy sourcing, and operational practices together rather than isolating one component [18]. For AI in energy systems, embodied impacts are especially important because sustainability claims become weaker if decarbonisation analytics depend on rapid hardware turnover and material-intensive infrastructure growth.

Extending hardware lifespan and reuse

Extending hardware lifespan and enabling reuse can reduce the life-cycle burden of AI systems by slowing replacement cycles and improving the environmental value obtained from existing infrastructure. ICT footprint research shows that digital sustainability depends not only on operational efficiency but also on patterns of production, consumption, and device turnover [6]. In sustainable AI governance, this implies that model development choices should avoid unnecessary dependence on the newest hardware when adequate performance could be achieved through efficient software, shared infrastructure, or right-sized deployment. Life-cycle responsibility therefore connects technical design to procurement, maintenance, repair, reuse, and responsible decommissioning.

Full life-cycle AI auditing

Full life-cycle AI auditing should assess whether an AI system's environmental costs are proportionate to its energy-system benefits across design, training, deployment, maintenance, and retirement. Life-cycle assessment research on AI

© 2025 The Author(s). | Published by Institute of Smart Energy Systems Press

applications identifies hidden environmental burdens that can be missed when analysis focuses only on direct model execution [19]. A credible audit would examine computational demand, carbon-aware scheduling potential, hardware requirements, data-centre dependence, software-induced hardware obsolescence, and end-of-life pathways. Such auditing should not be reduced to a narrow accounting exercise; it should function as a governance process that asks whether AI deployment advances sustainability goals without shifting burdens elsewhere.

Supply chain transparency and responsibility

Supply chain transparency is essential because AI hardware depends on global production networks, specialised components, rare materials, manufacturing capacity, and energy-intensive infrastructure. Studies of ICT emissions and digital-sector footprints show that environmental responsibility must account for the broader industrial systems that make digital computation possible [10]. Sustainable AI in energy systems should therefore require vendor disclosure, procurement standards, repairability expectations, and circular economy commitments that address both operational and embodied impacts. This is particularly important for critical energy infrastructure, where dependence on opaque AI supply chains may create environmental, geopolitical, and accountability risks.

Governance, Standards, and Accountability

Policy instruments for sustainable AI in energy

Policy instruments for sustainable AI in energy systems could include environmental reporting requirements, procurement standards, carbon-aware workload incentives, life-cycle disclosure mandates, and sector-specific guidance for critical infrastructure. Research on artificial intelligence and sustainability warns that AI can create systemic risks when governance fails to address indirect effects, rebound dynamics, and institutional incentives [12]. Reviews of AI-enabled energy optimisation further show that AI is becoming embedded across renewable energy, integrated energy systems, and operational decision-making, increasing the need for policy frameworks that assess both benefits and burdens [20]. Sustainable AI governance should therefore move beyond voluntary efficiency claims and require accountable design practices across utilities, vendors, regulators, and system operators.

Recent scholarship has also emphasised that sustainable AI governance in energy systems requires standardised environmental disclosure frameworks and operational transparency for AI infrastructure. Research examining environmental reporting and sustainability pathways for AI systems argues that institutions should disclose computational energy demand, embodied infrastructure impacts, and carbon-intensity characteristics across the AI deployment cycle in order to support accountable governance and policy evaluation [21]. In parallel, emerging studies on sustainable digital infrastructure suggest that integrating circular economy principles, adaptive resource allocation, and infrastructure-efficiency auditing into AI governance can improve the long-term environmental performance of energy-sector AI deployments while reducing hidden operational burdens [22].

Table 3 outlines key governance instruments that can operationalise sustainable AI principles across energy-sector institutions and infrastructure.

Table 3. Governance Instruments for Sustainable AI Deployment in Energy Systems

Governance Instrument	Primary Sustainability Objective	Institutional Application	Expected Sustainability Contribution
Mandatory AI Footprint Disclosure	Improve transparency of computational and environmental impacts	Utilities, regulators, AI vendors, and data-centre operators	Enables monitoring of operational emissions, embodied carbon, and infrastructure intensity

© 2025 The Author(s). | Published by Institute of Smart Energy Systems Press

Carbon-Aware Scheduling Standards	Align AI workloads with lower-carbon electricity availability	Grid operators, cloud providers, and energy analytics platforms	Reduces operational carbon emissions associated with AI computation
Sustainable Procurement Requirements	Integrate life-cycle responsibility into technology acquisition	Public utilities, governments, and infrastructure agencies	Encourages repairability, reuse, efficient hardware selection, and circular economy practices
Environmental AI Auditing	Evaluate full-system environmental impacts of AI deployment	Regulatory agencies and organisational governance units	Improves accountability for energy use, infrastructure expansion, and hardware turnover
Efficiency Benchmarking Frameworks	Assess proportionality between model complexity and operational value	AI developers, research institutions, and utilities	Discourages unnecessary computational expansion and promotes Green AI principles

Organisational accountability and reporting

Organisational accountability requires assigning responsibility for AI's environmental footprint across technical teams, procurement units, sustainability officers, and executive governance structures. Integrated energy-system research shows that AI can influence modelling, prediction, and decision-making across interconnected infrastructures, which means environmental responsibility should not be isolated within data-science teams [23]. Utilities and technology firms could establish internal review processes requiring justification of model complexity, assessment of carbon-aware scheduling potential, and life-cycle evaluation before deployment. Such accountability structures would be expected to make sustainable AI a routine governance obligation rather than an optional ethical add-on.

Evaluation Strategy for the Sustainable AI Framework

Conceptual adequacy and environmental integrity

The framework's conceptual adequacy can be evaluated by asking whether it captures the full environmental relationship between AI systems and the energy systems they are meant to improve. AI-enabled energy modelling and optimisation research shows that AI can contribute to forecasting, operational control, and planning, but these applications require sustainability evaluation beyond downstream system benefits [24]. Environmental integrity therefore depends on whether the framework prevents selective accounting, where operational gains are highlighted while computation, hardware, and infrastructure impacts remain invisible. A conceptually adequate sustainable AI framework should integrate computational efficiency, carbon-aware operation, and life-cycle responsibility as inseparable dimensions of environmental governance.

Practical feasibility and stakeholder acceptance

Practical feasibility depends on whether researchers, utilities, vendors, regulators, and infrastructure operators can apply the framework without undermining reliability or decision quality. Building energy prediction and energy consumption forecasting reviews show that AI methods are widely applied across operational contexts, but their adoption depends on usability, trust, and fit with institutional routines [25]. Stakeholder acceptance would therefore require sustainability requirements that are transparent, proportionate, and compatible with operational realities rather than imposed as abstract environmental ideals. The framework could be tested conceptually through pilots, procurement templates, reporting standards, and governance reviews that examine whether sustainability criteria can be incorporated into real AI development processes.

Scalability and adaptability

© 2025 The Author(s). | Published by Institute of Smart Energy Systems Press

Scalability and adaptability require the framework to remain useful across different energy contexts, including smart grids, buildings, renewable forecasting, demand response, energy markets, and critical infrastructure operations. Reviews of AI-based building energy prediction and power-system applications show that model types, data structures, and operational objectives vary substantially across energy domains [26]. Similarly, research on prosumers and next-generation electricity markets indicates that AI-enabled systems may operate across decentralised, interactive, and market-mediated environments [27]. The three-pillar framework is therefore designed as an adaptable governance structure rather than a single technical prescription, allowing each domain to specify its own balance among efficiency, carbon awareness, life-cycle responsibility, reliability, and public value.

Limitations

Data availability and measurement challenges

A major limitation of the framework is that precise AI carbon accounting can be difficult because data on hardware supply chains, electricity sources, model training practices, inference frequency, and data-centre operations may be incomplete or inaccessible. Research on estimating AI carbon footprints shows that environmental assessment often depends on assumptions about energy sources, infrastructure, and deployment patterns, which can make results uncertain even when the conceptual need for accounting is clear [8]. Energy-system AI applications also vary widely in latency, scale, and operational context, making standardised measurement difficult across use cases [28]. The framework therefore provides a conceptual structure for responsible evaluation, but its implementation would require better disclosure, measurement tools, and institutional capacity.

Rapid technological evolution

A second limitation is that AI hardware, software, data-centre design, and energy-system applications evolve quickly, making sustainable AI a moving target. Research on sustainable AI servers and net-zero pathways suggests that future environmental outcomes will depend on technology design, electricity decarbonisation, infrastructure choices, and governance decisions that remain uncertain [29]. Advances in efficient architectures may reduce the burden of some AI tasks, while the expansion of AI deployment could increase total demand through rebound effects and broader adoption. Sustainable AI governance must therefore remain adaptive, updating its assumptions as technologies, energy systems, and environmental standards change.

Conclusion

Sustainable AI in energy systems requires a framework that addresses AI's dual role as both an enabler of energy-system optimisation and a consumer of energy, materials, and infrastructure. This article proposed a three-pillar framework centred on computational efficiency, carbon-aware algorithms, and life-cycle responsibility. Together, these pillars provide a conceptual basis for designing AI systems whose environmental footprint is minimised and whose deployment is aligned with broader sustainability goals. The framework emphasises that AI should not be considered sustainable merely because it is applied to an energy problem.

The central implication is that AI's environmental costs must be internalised into design, procurement, operation, and governance. Computational efficiency asks whether the model is proportionate to the task. Carbon-aware algorithms ask whether computation can be aligned with low-carbon electricity availability. Life-cycle responsibility asks whether the hardware, infrastructure, and supply-chain impacts of AI are being governed rather than ignored.

Future progress requires integrated action from AI researchers, energy-system operators, technology firms, regulators, and sustainability professionals. Researchers should design models that are efficient, transparent, and environmentally accountable. Industry actors should disclose and govern the footprint of AI across its full life cycle. Policymakers should

© 2025 The Author(s). | Published by Institute of Smart Energy Systems Press

create incentives and standards that ensure AI contributes positively to the energy transition rather than expanding the environmental burdens it is intended to reduce.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 01 Nov 2023 Revised: 07 Jan 2024 Accepted: 24 Jan 2024
Published online: 15 June 2025

Rights and permissions

Open Access The author(s) retain copyright. This article is licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. It may be shared and adapted for non-commercial purposes with appropriate attribution, an indication of changes, and distribution of adaptations under the same license. Third-party material may be subject to separate terms identified in its credit line. View the license at https://creativecommons.org/licenses/by-nc-sa/4.0/.

References

1. Schwartz R, Dodge J, Smith NA, Etzioni O, Recht B. Green AI. Commun ACM. 2020;63(12):54-63.
2. Dhar P. The carbon impact of artificial intelligence. Nat Mach Intell. 2020;2(8):423-5. https://doi.org/10.1038/s42256-020-0219-9.
3. Donti PL, Kolter JZ. Machine learning for sustainable energy systems. Annu Rev Environ Resour. 2021;46(1):719-47. https://doi.org/10.1146/annurev-environ-020220-061831.
4. Bose BK. Artificial intelligence techniques in smart grid and renewable energy systems—some example applications. Proc IEEE. 2017;105(11):2262-73.
5. Radovanović A, Koningstein R, Schneider I, Chen B, Duarte A, Roy B, et al. Carbon-aware computing for datacenters. IEEE Trans Power Syst. 2023;38(2):1270-80.
6. Freitag C, Berners-Lee M, Widdicks K, Knowles B, Blair GS, Friday A. The real climate and transformative impact of ICT: a critique of estimates, trends, and regulations. Patterns (N Y). 2021;2(9):100340.

https://doi.org/10.1016/j.patter.2021.100340.

7. Van Wynsberghe A. Sustainable AI: AI for sustainability and the sustainability of AI. AI Ethics. 2021;1(3):213-8.

8. Luccioni AS, Viguier S, Ligozat AL. Estimating the carbon footprint of BLOOM, a 176B parameter language model. J Mach Learn Res. 2023;24(253):1-15.

9. Toosi AN, Qu C, de Assunção MD, Buyya R. Renewable-aware geographical load balancing of web applications for sustainable data centers. J Netw Comput Appl. 2017;83:155-68. https://doi.org/10.1016/j.jnca.2017.01.036.

10. Belkhir L, Elmeligi A. Assessing ICT global emissions footprint: trends to 2040 & recommendations. J Clean Prod. 2018;177:448-63. https://doi.org/10.1016/j.jclepro.2017.12.239.

11. Malmodin J, Lundén D. The energy and carbon footprint of the global ICT and E&M sectors 2010-2015. Sustainability. 2018;10(9):3027. https://doi.org/10.3390/su10093027.

12. Galaz V, Centeno MA, Callahan PW, Causevic A, Patterson T, Brass I, et al. Artificial intelligence, systemic risks, and sustainability. Technol Soc. 2021;67:101741. https://doi.org/10.1016/j.techsoc.2021.101741.

13. Ligozat AL, Lefevre J, Bugeau A, Combaz J. Unraveling the hidden environmental impacts of AI solutions: the AI footprint. Sustainability. 2022;14(9):5172.

14. Omitaomu OA, Niu H. Artificial intelligence techniques in smart grid: a survey. Smart Cities. 2021;4(2):548-68.

15. Forootan MM, Larki I, Zahedi R, Ahmadi A. Machine learning and deep learning in energy systems: a review. Sustainability. 2022;14(8):4832.

16. Kaack LH, Donti PL, Strubell E, Kamiya G, Creutzig F, Rolnick D. Aligning artificial intelligence with climate change mitigation. Nat Clim Change. 2022;12(6):518-27. https://doi.org/10.1038/s41558-022-01377-7.

17. Wang Q, Li Y, Li R. Integrating artificial intelligence in energy transition: a comprehensive review. Energy Strateg Rev. 2025;57:101600. https://doi.org/10.1016/j.esr.2024.101600.

18. Cao Z, Zhou X, Wu X, Zhu Z, Liu TX, Neng J, et al. Data center sustainability: revisits and outlooks. IEEE Trans Sustain Comput. 2024;9(3):236-48. https://doi.org/10.1109/TSUSC.2023.3281583.

19. Plociennik C, Watjanatepin P, van Acker K, Ruskowski M. Life cycle assessment of artificial intelligence applications: research gaps and opportunities. Procedia CIRP. 2025;135:924-9. https://doi.org/10.1016/j.procir.2025.01.079.

20. Shoaei M, Noorollahi Y, Hajinezhad A, Moosavian SF. A review of the applications of artificial intelligence in renewable energy systems: an approach-based study. Energy Convers Manag. 2024;306:118207. https://doi.org/10.1016/j.enconman.2024.118207.

21. Crawford K, Joler V. Anatomy of an AI system: the Amazon Echo as an anatomical map of human labor, data and planetary resources. New York: AI Now Institute; 2018.

© 2025 The Author(s). | Published by Institute of Smart Energy Systems Press

22. Gupta U, Kim YG, Lee S, Tse J, Lee HH, Wei GY, et al. Chasing carbon: the elusive environmental footprint of computing. In: Proceedings of the 2021 IEEE International Symposium on High-Performance Computer Architecture (HPCA); 2021 Feb 27-Mar 3; Seoul, South Korea. IEEE; 2021. p.854-67.

23. Alabi TM, Aghimien EI, Agbajor FD, Yang Z, Lu L, Adeoye AR, et al. A review on the integrated optimization techniques and machine learning approaches for modeling, prediction, and decision making on integrated energy systems. Renew Energy. 2022;194:822-49.

24. Lin Y, Tang J, Guo J, Wu S, Li Z. Advancing AI-enabled techniques in energy system modeling: a review of data-driven, mechanism-driven, and hybrid modeling approaches. Energies. 2025;18(4):845.

25. Mat Daut MA, Hassan MY, Abdullah H, Rahman HA, Abdullah MP, Hussin F. Building electrical energy consumption forecasting analysis using conventional and artificial intelligence methods: a review. Renew Sustain Energy Rev. 2017;70:1108-18. https://doi.org/10.1016/j.rser.2016.12.015.

26. Wang Z, Srinivasan RS. A review of artificial intelligence based building energy use prediction: contrasting the capabilities of single and ensemble prediction models. Renew Sustain Energy Rev. 2017;75:796-808.

27. Chen T, Alsafasfeh Q, Pourbabak H, Su W. The next-generation U.S. retail electricity market with customers and prosumers—a bibliographical survey. Energies. 2018;11(1):8. https://doi.org/10.3390/en11010008.

28. Pandey U, Pathak A, Kumar A, Mondal S. Applications of artificial intelligence in power system operation, control and planning: a review. Clean Energy. 2023;7(6):1199-218.

29. Xiao T, Fuso Nerini F, Matthews HD, Tavoni M, You F. Environmental impact and net-zero pathways for sustainable artificial intelligence servers in the USA. Nat Sustain. 2025;8:1541-53. https://doi.org/10.1038/s41893-025-01681-y.

© 2025 The Author(s). | Published by Institute of Smart Energy Systems Press