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AI-Orchestrated Net-Zero Energy Systems: A Conceptual Model for Carbon Intelligence, Grid Flexibility, and Multi-Level Governance

Wouter De Smet[1*], Liesbeth Van Dam[1], Pieter Janssens[2]

Abstract

Net-zero energy systems require coordinated action across distributed energy resources, storage, flexible demand, carbon constraints, electricity markets, and governance institutions. Artificial intelligence is increasingly presented as a system-level capability for aligning operational energy decisions with decarbonization goals, yet current discussions often treat AI-enabled energy management, carbon accounting, grid flexibility, and governance as separate domains. This fragmentation limits understanding of how AI can support carbon-aware flexibility across technical and institutional scales. This article develops a conceptual model of AI-orchestrated net-zero energy systems by synthesizing literature on AI in energy systems, carbon-aware operations, flexibility management, and multi-level governance. The article does not report experiments, simulations, datasets, or empirical performance results; instead, it offers a theoretical framework for understanding AI as a socio-technical coordination architecture. The proposed model is organized around three interacting pillars: carbon intelligence, grid flexibility, and multi-level governance. Carbon intelligence enables the interpretation of emissions signals, carbon intensity variation, lifecycle constraints, and decarbonization priorities. Grid flexibility links these signals to demand response, storage dispatch, distributed generation, load shifting, and system-balancing mechanisms. Multi-level governance establishes the institutional conditions under which AI-supported coordination can remain transparent, accountable, reliable, and aligned with public decarbonization objectives. Four analytical tables further specify the model pillars, carbon intelligence functions, flexibility orchestration mechanisms, and governance architecture. The article argues that AI-orchestrated net-zero energy systems should not be understood as purely technical optimization platforms, but as governed coordination systems that connect carbon-aware intelligence with flexible grid resources and institutional oversight across local, national, and international levels. Its contribution is to clarify how AI can support net-zero alignment when technical optimization is embedded within accountable governance and carbon-sensitive decision structures.

Keywords Grid flexibility, AI orchestration, Net-zero energy systems, Carbon intelligence, Multi-level governance, Conceptual model

*Correspondence:
Wouter De Smet
wouter.desmet@kuleuven.be
[1] Department of Artificial Intelligence for Smart Grid Stability, Faculty of Engineering, KU Leuven, Leuven, Belgium
[2] Department of Intelligent Energy Networks and Data Science, Faculty of Engineering, Ghent University, Ghent, Belgium

Introduction

Net-zero energy systems require coordination across increasingly distributed, digitalized, and carbon-constrained infrastructures. Digital technologies are expected to support this transition by linking energy planning, operational control, and decarbonization objectives across complex system boundaries [1]. AI has become central to this debate because

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sustainable energy transitions now involve forecasting, optimization, learning, and adaptive decision support across many interacting assets [2]. The challenge is not only to decarbonize generation, but also to coordinate millions of flexible loads, distributed resources, carbon signals, and governance rules in near real time.

AI is uniquely positioned to contribute to this coordination because machine learning can support prediction, classification, optimization, and adaptive control in energy systems [3]. Demand-side response studies show how AI can improve the matching of flexible consumption with grid needs, yet this literature often remains focused on operational efficiency rather than system-wide carbon alignment [4]. Similarly, building load prediction research has advanced AI-based forecasting, but such forecasting is frequently treated as a technical input rather than part of a broader net-zero governance architecture [5]. The result is a compartmentalized research landscape in which carbon intelligence, grid flexibility, and governance are rarely conceptualized as mutually dependent pillars.

An integrative model is needed because carbon-aware energy operation cannot be achieved through isolated optimization of individual assets or sectors. Reviews of machine learning in energy systems demonstrate the breadth of AI applications, but also reveal the need for frameworks that connect technical intelligence to system-level transition goals [6]. Virtual power plant research shows how aggregation platforms can coordinate distributed resources, yet these platforms must be connected to carbon accounting, institutional oversight, and justice concerns if they are to support net-zero rather than only short-term balancing [7]. The model developed here therefore treats AI orchestration as a cross-scale coordination function linking carbon intelligence, flexibility activation, and governance responsibility.

This article contributes a conceptual model for AI-orchestrated net-zero energy systems. It builds on research on virtual power plants, flexibility, carbon-aware operation, socio-technical transitions, and energy justice to specify how AI could be governed as a coordinating layer rather than as an autonomous substitute for public decision-making [8]. The model is designed for conceptual clarification, not empirical validation, and it identifies the functions, boundaries, risks, and governance arrangements that would be expected to shape AI-enabled net-zero systems. By doing so, it provides a foundation for future system design, policy experimentation, and interdisciplinary evaluation.

Background

The net-zero challenge: system integration and scale

The net-zero challenge is fundamentally a problem of system integration across technologies, institutions, and time scales. High-renewable systems require flexibility indicators that can track whether resources, markets, and operational practices are becoming capable of balancing variable supply and demand [9]. Flexibility provision must also be quantified in ways that distinguish technical capacity from usable, locationally relevant, and temporally available flexibility [10]. Without orchestrated intelligence, energy systems may experience coordination failures in which carbon-reducing actions in one subsystem create congestion, inequity, or inefficiency elsewhere.

AI orchestration: from smart grids to system-of-systems

AI in energy systems has evolved from forecasting and single-device optimization toward platform-based orchestration across distributed assets. Virtual power plant literature illustrates this shift by framing distributed energy resources, storage, and controllable loads as coordinated portfolios rather than isolated technologies [8]. Next-generation virtual power plant frameworks further suggest that AI-enabled aggregation could support market participation, real-time dispatch, and system services across heterogeneous assets [11]. In a net-zero context, however, such orchestration must be directed by carbon, reliability, and governance objectives rather than by economic optimization alone.

Recent systematic reviews have confirmed that while machine learning models such as CNNs, LSTMs, and GRUs have achieved high accuracy in energy forecasting, there exists a critical research gap regarding the computational energy cost and associated carbon emissions of the AI models themselves [12]. This dual-assessment approach, which balances

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predictive performance against eco-efficiency, is essential for ensuring that the AI orchestration layer does not undermine the net-zero objectives it is designed to support [13]. Furthermore, emerging governance frameworks for high-risk energy systems are beginning to codify these requirements, mandating that AI applications in critical infrastructure include verifiable human rights impact assessments and dynamic audit trails to ensure algorithmic accountability.

Carbon intelligence: real-time and life-cycle perspectives

Carbon intelligence can be conceptualized as the capacity to estimate, attribute, forecast, and operationalize carbon information across energy decisions. Machine learning-based carbon emission forecasting shows how regional electricity systems may be represented through predictive carbon signals that inform day-ahead planning [14]. Carbon-aware scheduling research further indicates that operational decisions can be structured around predicted carbon consequences rather than treating emissions as retrospective accounting outputs [15]. A complete carbon intelligence layer should also include life-cycle and embodied carbon perspectives, because net-zero systems depend on both operational emissions and infrastructure-related carbon burdens.

Grid flexibility: technologies, markets, and coordination

Grid flexibility includes demand response, storage, electric vehicles, sector coupling, flexible buildings, industrial load shifting, and aggregated distributed energy resources. Industrial demand-side flexibility has been linked to a just energy transition because flexible operation can affect industrial competitiveness, labour conditions, and regional development pathways [16]. Integrated energy system perspectives also show that residential and transport flexibility must be evaluated across sectors rather than only within electricity markets [17]. AI orchestration can therefore be conceptualized as a mechanism for forecasting, aggregating, activating, and settling flexibility while accounting for carbon consequences and governance constraints.

Multi-level governance of energy and AI

Multi-level governance is central to net-zero energy systems because decisions about infrastructure, markets, carbon accounting, and justice are distributed across local, national, and international arenas. Socio-technical transition theory emphasizes that low-carbon transitions involve interacting technologies, user practices, markets, policies, and cultural expectations rather than linear technological substitution [18]. Energy transition research also indicates that the next phase of transition requires stronger attention to policy coordination, institutional legitimacy, and system integration [19]. For AI-orchestrated systems, multi-level governance must define who sets objectives, who validates carbon signals, who controls algorithms, and who remains accountable for consequences.

Conceptual Foundation

Orchestration as an integrative concept

Orchestration refers here to the intelligent coordination of semi-autonomous actors, assets, markets, and institutions toward shared system-level goals. Unlike top-down control, orchestration does not presume that all resources are centrally owned or uniformly governed; instead, it aligns distributed actions through data, prediction, incentives, standards, and accountability mechanisms. Policy process research suggests that sustainability transitions require attention to institutions, coalitions, rules, and political contestation, which means that AI orchestration must be embedded in governance rather than treated as purely technical coordination [20]. The model therefore defines orchestration as a socio-technical capability that combines computational intelligence with legitimate rule-making and oversight.

The three pillars of the model

The model is organized around three pillars: Carbon Intelligence, Grid Flexibility, and Multi-Level Governance. Carbon Intelligence provides the carbon-aware information layer that allows operational decisions to be evaluated against net-

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zero objectives; Grid Flexibility provides the controllable resource base through which the system can respond; and Multi-Level Governance defines the institutional rules, accountability structures, and legitimacy conditions that guide AI-enabled coordination. Transformation governance research shows that sustainability transitions are shaped by politics, institutional change, and contested priorities, making governance integral to the technical design of net-zero systems [13]. The three pillars are therefore interdependent: carbon intelligence without flexibility lacks operational agency, flexibility without governance risks inequitable control, and governance without AI-enabled intelligence may be too slow for real-time coordination.

System boundaries and model scope

The proposed model covers AI-enabled coordination from local distributed energy resources and community flexibility markets to national grid planning, carbon market integration, and international climate governance alignment. It includes operational carbon signals, life-cycle carbon attribution, demand-side flexibility, virtual aggregation, policy coordination, accountability, and justice, but it does not claim to replace existing planning institutions or regulatory mandates. Clean energy transition justice research shows that decarbonization strategies can distribute costs and benefits unevenly, so the model explicitly includes equity and accountability within its system boundary [21].

Figure 1 shows that the three pillars are interdependent: carbon intelligence without flexibility lacks operational agency, flexibility without governance risks inequitable control, and governance without AI-enabled intelligence may be too slow for real-time coordination.

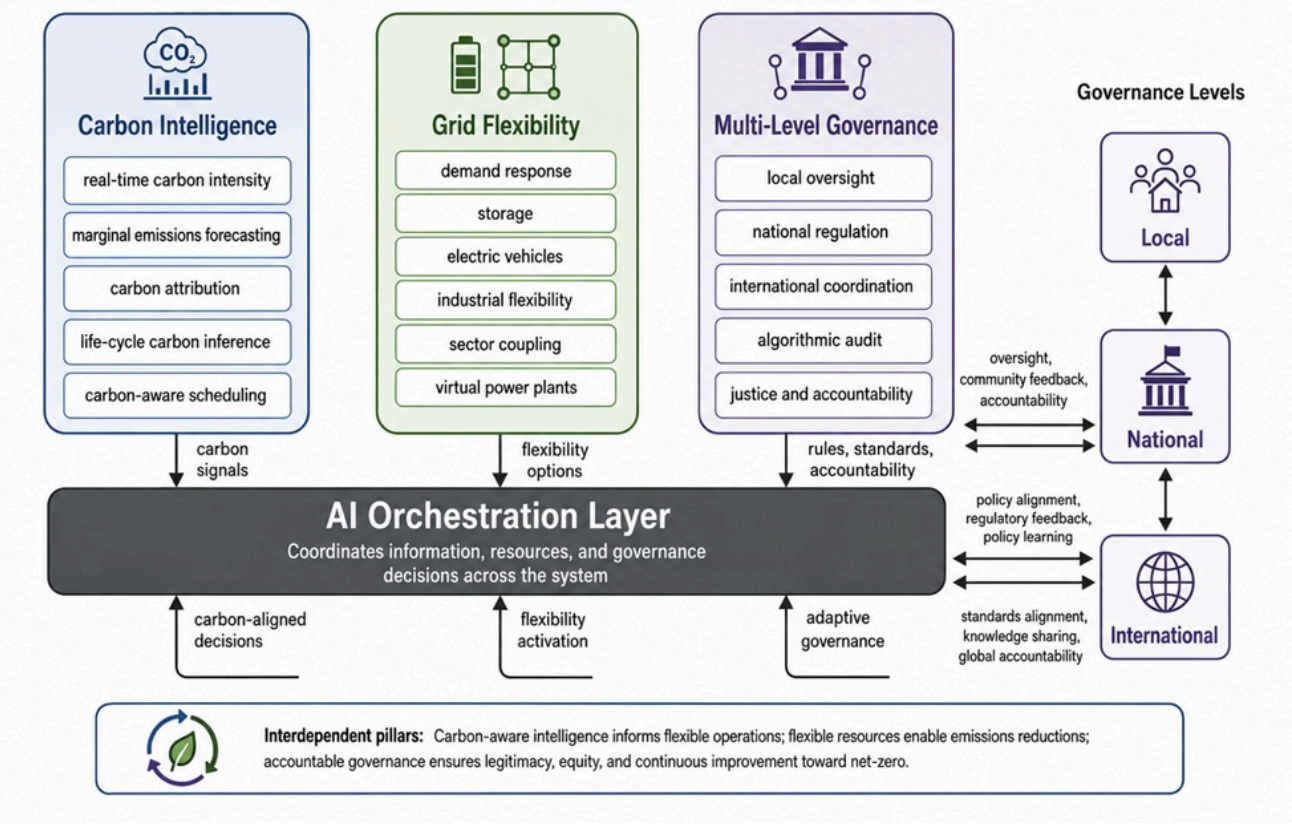


Figure 1. Multi-Level Net-Zero Governance Framework

As shown in **Table 1**, the model's three pillars are analytically distinct but functionally coupled through AI orchestration.

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Table 1. Integrated AI-Orchestrated System Model for Carbon Intelligence, Grid Flexibility, and Multi-Level Governance in Clean Energy Transition Systems

Pillar	Definition	Core AI Functions	Key Outcomes
Carbon Intelligence	A carbon-aware information layer that converts operational, market, and life-cycle data into actionable carbon signals.	Carbon intensity estimation, marginal emissions forecasting, life-cycle inference, carbon attribution, carbon-aware scheduling.	Decisions become aligned with temporal, spatial, and embodied carbon consequences rather than average annual emissions alone.
Grid Flexibility	The coordinated capacity of distributed and centralized resources to shift, store, convert, or curtail energy use and supply.	Flexibility forecasting, resource aggregation, multi-agent dispatch, constraint-aware optimization, settlement support.	Flexibility becomes available as a carbon-aligned system service rather than only as a reliability or price-response mechanism.
Multi-Level Governance	The institutional architecture that defines objectives, rules, oversight, accountability, and coordination across scales.	Policy monitoring, regulatory scenario analysis, compliance analytics, audit trails, participatory decision support.	AI orchestration remains legitimate, accountable, and adaptable across local, national, and international governance contexts.

Carbon Intelligence: AI for Carbon-Aware Energy Systems

Real-time carbon intensity tracking and forecasting

Real-time carbon intensity tracking allows AI systems to differentiate between energy use that appears identical in quantity but differs in carbon consequence. Day-ahead carbon emission forecasting demonstrates how machine learning could support operational awareness of regional carbon variation, enabling system operators and aggregators to anticipate when flexible resources should be activated [14]. Carbon-aware distribution scheduling further suggests that forecasting and optimization can be fused so that carbon signals influence dispatch decisions before emissions occur [15]. In the proposed model, real-time carbon tracking functions as the sensing layer through which AI orchestration interprets the carbon state of the energy system.

Carbon attribution and life-cycle assessment with AI

Carbon attribution extends carbon intelligence beyond real-time grid emissions by assigning carbon responsibility across assets, sectors, supply chains, and energy vectors. Reviews of emission factor-based methods show that electricity carbon accounting depends heavily on methodological choices, including average versus marginal factors, temporal granularity, and boundary definitions [22]. Flow-based power grid carbon accounting further indicates that carbon responsibility can be traced through networked electricity flows, which is essential when local consumption depends on remote generation and interregional exchanges [23]. AI-supported life-cycle assessment may complement these methods by helping estimate embodied and operational carbon across complex technologies, although such approaches require careful validation and transparent assumptions [24].

Table 2 summarizes the key governance gaps and AI-specific risks identified in the literature for net-zero energy systems.

Table 2. Policy Recommendations and Governance Gaps for AI Orchestration in Net-Zero Energy Systems

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Governance Domain	Identified Gap/Risk	Proposed AI-Specific Intervention
System Reliability	Lack of interoperability standards for AI-driven DER coordination.	Mandate transparent validation and stress-testing protocols for black-box models.
Algorithmic Accountability	Inability to audit automated grid control decisions in real-time.	Require explainable AI (XAI) mechanisms and human-in-the-loop mandates.
Carbon Efficiency	High computational energy cost of forecasting models (e.g., LSTM/GRU).	Mandate energy efficiency benchmarks for AI models; incentivize low-energy AI development.
Market & Regulation	Ambiguous liability when AI agents execute conflicting market trades.	Define the scope of AI autonomy in energy markets; expand oversight to include AI-specific trading rules.

Carbon-aware optimization of energy operations

Carbon-aware optimization can be conceptualized as the translation of carbon intelligence into operational decisions for load shifting, storage charging, generation dispatch, electric vehicle coordination, and energy trading. Carbon-aware scheduling in manufacturing shows how operational timing could be adjusted to reduce greenhouse gas exposure without assuming that carbon outcomes are fixed by annual consumption alone [25]. Research on carbon-free electricity frameworks similarly indicates that decarbonization requires matching consumption and supply through temporally and spatially meaningful carbon information [23]. **Table 3** maps how different carbon intelligence dimensions could be operationalized through AI techniques while also identifying limitations that must be governed.

Table 3. AI-Enabled Operationalization of Carbon Intelligence for Carbon-Aware Energy System Optimization

Carbon Intelligence Dimension	AI Technique	Data Sources	Operationalization in Energy System	Limitation
Real-time carbon intensity estimation	Supervised learning and probabilistic state estimation	Generation mix, interconnector flows, dispatch data, weather, demand profiles	Produces dynamic carbon signals for operators, aggregators, buildings, and flexible loads.	Accuracy depends on data granularity, dispatch transparency, and treatment of marginal emissions.
Marginal emissions forecasting	Time-series forecasting and ensemble learning	Historical emissions, forecast demand, renewable forecasts, unit commitment indicators	Anticipates the carbon effect of shifting load or charging storage across time windows.	Forecasts may be unstable during scarcity events, curtailment, or cross-border congestion.
Carbon attribution across networks	Graph-based learning and flow tracing	Grid topology, power flows, market zones, bilateral exchanges	Allocates carbon responsibility to consumption nodes, sectors, or market participants.	Attribution rules may be contested because physical flows, contractual claims, and policy accounting differ.
Life-cycle carbon	Machine learning-assisted life-cycle	Technology inventories, supply-	Links operational decisions to embodied carbon implications	Life-cycle estimates may embed uncertain

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inference	assessment	chain databases, material profiles, asset metadata	of infrastructure and technology choices.	supplier data and incomplete boundary assumptions.
Carbon-aware operational scheduling	Reinforcement learning and constrained optimization	Carbon forecasts, prices, flexibility availability, user constraints, grid constraints	Coordinates load, storage, distributed generation, and trading according to carbon and reliability priorities.	Optimization can create rebound, inequity, or gaming unless objectives and constraints are transparent.

Grid Flexibility and AI Orchestration

Flexibility resource typology and coordination complexity

Grid flexibility resources differ not only by technology but also by temporal responsiveness, ownership structure, spatial location, user acceptability, and carbon effect. Reviews of transition pathway modelling show that flexibility must be represented across supply, demand, storage, sector coupling, and infrastructure expansion rather than as a single balancing resource [26]. Demand-side flexibility in residential and transport sectors illustrates this complexity because household devices, electric vehicles, and mobility patterns respond to different incentives and constraints [17]. In the proposed model, AI orchestration must therefore classify flexibility by operational usefulness, carbon consequence, governance requirements, and social legitimacy.

AI for flexibility forecasting, aggregation, and dispatch

AI can support flexibility management through forecasting availability, aggregating small resources, coordinating dispatch, and adapting decisions under uncertainty. Building load prediction research provides a foundation for estimating flexible demand in buildings, while demand-side response studies show how AI can infer patterns of responsiveness and automate control decisions [4, 5]. Virtual power plant taxonomies further demonstrate how machine learning can coordinate distributed resources across home, building, and portfolio scales [7]. These functions may enable a system-of-systems approach in which AI agents coordinate diverse assets while remaining constrained by grid security, carbon intelligence, and governance rules.

Carbon-aligned flexibility activation

Carbon-aligned flexibility activation means that AI should not activate resources solely because they are available, inexpensive, or useful for balancing; it should evaluate whether their activation advances net-zero goals. Industrial flexibility may support decarbonization when it shifts demand toward lower-carbon periods, but it may also create distributional concerns if costs are transferred to specific firms, workers, or regions [16]. Energy-intensive AI itself also creates new electricity demand, making carbon-aware orchestration necessary not only for energy consumers but also for the computational systems that manage them [27]. As shown in **Table 4**, the model classifies flexibility resources by their coordination challenge, AI mechanism, carbon intelligence integration, and governance implication.

Table 4. AI-Orchestrated Carbon-Aligned Flexibility Resources: Coordination Mechanisms, Carbon Intelligence, and Governance Implications

Flexibility Resource	Orchestration Challenge	AI Coordination Mechanism	Carbon Intelligence Integration	Governance Implication
Residential flexible loads	High volume, low individual capacity,	Federated or privacy-preserving demand	Activates appliances or heating shifts only when	Requires consumer consent, data

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	privacy-sensitive user behaviour	response prediction and automated scheduling	forecast carbon intensity and user constraints align.	minimization, and protection against unequal burden shifting.
Commercial buildings	Occupancy-dependent flexibility and comfort constraints	Load forecasting, model predictive control, and portfolio aggregation	Uses carbon forecasts to pre-cool, pre-heat, or defer non-critical loads without compromising service quality.	Requires transparent rules for occupant comfort, tenant rights, and energy performance accountability.
Industrial processes	Production constraints, competitiveness concerns, and regional employment implications	Constraint-aware optimization and production-flexibility scheduling	Aligns process timing with low-carbon electricity while preserving operational feasibility.	Requires just transition safeguards and sector-specific compensation or market design.
Electric vehicles	Mobile storage, uncertain availability, distribution network constraints	Multi-agent charging coordination and vehicle-to-grid scheduling	Charges when carbon intensity is low and discharges only when grid and carbon benefits are credible.	Requires standards for user control, battery degradation compensation, and infrastructure access equity.
Stationary storage	Ambiguous carbon effect depending on charge and discharge timing	Reinforcement learning with carbon-constrained dispatch	Prevents storage from charging during high-carbon periods and discharging in ways that displace cleaner supply.	Requires market rules that reward carbon-aligned flexibility rather than arbitrage alone.
Sector coupling assets	Cross-vector interdependence among electricity, heat, hydrogen, and fuels	Integrated energy system optimization and scenario-aware control	Uses carbon signals across energy vectors to avoid shifting emissions between sectors.	Requires intersectoral governance and harmonized carbon accounting rules.
Virtual power plants	Heterogeneous ownership, market participation, and settlement complexity	Aggregation platforms, resource clustering, and automated bidding	Embeds carbon criteria into bids, dispatch priorities, and flexibility settlement.	Requires auditability of aggregator algorithms and prevention of carbon-accounting manipulation.

Multi-Level Governance for Net-Zero AI Systems

Governance functions across local, national, and international levels

AI-orchestrated net-zero systems require governance functions to be distributed across levels without fragmenting responsibility. Local actors may govern community flexibility, building automation, municipal energy planning, and consumer participation, while national institutions typically define market rules, grid codes, carbon accounting standards, and infrastructure investment priorities [19]. International frameworks shape carbon reporting norms, climate commitments, and cross-border coordination, especially where electricity trade and technology supply chains extend beyond national boundaries [13]. The model therefore treats governance as a layered coordination architecture rather than a single regulatory intervention.

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Polycentric governance of AI-orchestrated energy systems

Polycentric governance is useful for AI-orchestrated energy systems because no single authority can fully control distributed energy assets, carbon markets, digital platforms, and climate commitments across all scales. Sustainability transition governance research shows that transformation involves multiple centres of authority, contested priorities, and evolving institutional arrangements [13]. In this model, AI agents, grid operators, aggregators, regulators, municipalities, and international bodies interact through overlapping rules, standards, markets, and accountability mechanisms. Such polycentric coordination may increase adaptability, but it also requires safeguards against institutional gaps, duplicated authority, and accountability dilution.

AI for policy coordination and adaptive governance

AI tools could support adaptive governance by monitoring policy interactions, identifying regulatory conflicts, evaluating carbon accounting inconsistencies, and informing scenario-based policy learning. Machine learning for climate action has been framed as a cross-sectoral enabling capability, but its use in governance should remain bounded by public accountability and democratic oversight [28]. Environmental assessments of AI infrastructure also show that AI systems themselves create energy and carbon burdens, meaning policy coordination must govern both AI for net-zero and the net-zero performance of AI [12]. **Table 5** presents the governance architecture of the model by linking governance levels, AI tools, coordination mechanisms, and accountability structures.

Table 5. AI-Enabled Adaptive Governance Architecture for Multi-Level Net-Zero Energy and Climate Coordination

Governance Level	Governance Function	AI Tool/System	Coordination Mechanism	Accountability Structure
Local	Community flexibility coordination, municipal energy planning, building and mobility integration	Local flexibility platforms, building energy AI, community carbon dashboards	Links household, municipal, and distribution-level decisions to local carbon and reliability goals	Municipal oversight, community participation, consent rules, local data governance
Local	Distribution network congestion and equity monitoring	AI-enabled distribution planning and locational flexibility analytics	Coordinates distributed energy resources, electric vehicles, and demand response within grid constraints	Distribution system operator audits, consumer protection bodies, public reporting
National	Electricity market design, grid code development, carbon accounting standards	National carbon intelligence platforms and market surveillance analytics	Aligns flexibility markets, carbon signals, grid planning, and regulatory compliance	Energy regulators, independent system operators, legislative mandates, algorithmic audit requirements
National	Infrastructure planning and sector coupling governance	Integrated energy system modelling and policy scenario tools	Connects electricity, heat, transport, hydrogen, industry, and storage planning under net-zero objectives	Public planning agencies, judicial review, transparent consultation, procurement accountability

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International	Cross-border carbon accounting and electricity trade alignment	Interoperable carbon accounting systems and cross-border data exchange tools	Harmonizes emissions factors, certification rules, and electricity trade claims across jurisdictions	International reporting frameworks, treaty-based commitments, peer review processes
International	Climate policy coordination and technology governance	AI-assisted policy comparison and global decarbonization monitoring tools	Identifies policy gaps, carbon leakage risks, and uneven technology impacts across countries	Multilateral institutions, national reporting obligations, civil society scrutiny

Ensuring accountability and justice across scales

Accountability becomes difficult when AI orchestration spans household devices, aggregators, grid operators, national regulators, and international carbon systems. Clean energy transition scholarship warns that decarbonization may reproduce or intensify inequities when benefits and burdens are unevenly distributed [21]. Multi-level governance research further shows that coordination problems can become wicked when justice, power, and responsibility are contested across institutional scales [21]. The proposed model therefore requires audit trails, explainable decision rules, participatory oversight, and appeal mechanisms to prevent carbon optimization from becoming a justification for opaque or unjust control.

Model Integration and System Dynamics

Interactions among the three pillars

The three pillars interact through continuous information, decision, and governance flows. Carbon Intelligence informs which actions are carbon-aligned, Grid Flexibility determines which actions are technically available, and Multi-Level Governance defines which actions are legitimate, accountable, and institutionally acceptable [9]. Virtual power plant research illustrates how distributed assets can be aggregated into coordinated portfolios, but the model extends this logic by requiring carbon intelligence and governance constraints to shape aggregation and dispatch [8]. The resulting system can be conceptualized as an orchestration architecture in which AI links sensing, prediction, decision support, oversight, and institutional feedback.

Dynamic orchestration under uncertainty and change

Net-zero energy systems must operate under uncertainty in renewable generation, demand behaviour, carbon prices, technology costs, infrastructure constraints, and policy direction. Machine learning methods in energy systems are useful because they can adapt to changing data patterns, but their outputs remain contingent on assumptions, training conditions, and institutional contexts [6]. Policy process theory also suggests that governance systems evolve through conflict, learning, coalition-building, and institutional revision rather than through stable linear implementation [20]. The proposed model therefore treats orchestration as adaptive but governable, requiring periodic recalibration of AI objectives, carbon metrics, market rules, and accountability procedures.

Emergent behaviour and systemic risk

AI-orchestrated energy systems may generate emergent behaviour when many autonomous or semi-autonomous agents respond simultaneously to similar price, grid, or carbon signals. Demand-side response literature shows that automated flexibility can improve coordination, yet widespread automation may also create synchronization risks, rebound effects, or new vulnerabilities if incentives are poorly designed [4]. Research on the growing energy footprint of AI adds another systemic concern: the digital infrastructure needed to coordinate net-zero systems may itself increase electricity demand

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and carbon pressure if unmanaged [27]. The model therefore requires guardrails such as diversity of control strategies, stress testing, human oversight, fail-safe operation, and carbon-aware computing rules.

Illustrative scenarios of orchestrated net-zero operation

In a winter evening scarcity scenario, the model would use carbon forecasts, flexibility availability, and governance constraints to decide whether to shift heating loads, discharge storage, activate industrial flexibility, or import electricity. In a high-renewable surplus scenario, AI could coordinate electric vehicle charging, hydrogen production, thermal storage, and industrial processes while ensuring that carbon accounting rules avoid double-counting low-carbon claims [26]. In a cross-border trading scenario, carbon attribution methods would help distinguish physical electricity flows from contractual claims, while governance institutions would determine which carbon signals are valid for settlement [22]. These scenarios are illustrative only, but they show how the model could connect operational flexibility, carbon intelligence, and multi-level oversight without reporting simulated outcomes.

Policy, Institutional, and Ethical Implications

Designing institutions for AI-orchestrated net-zero

Institutions for AI-orchestrated net-zero systems should be designed to govern algorithms, data infrastructures, carbon signals, and flexibility markets as interconnected public-interest systems. Energy transition research indicates that the next phase of decarbonization requires stronger attention to integration, coordination, and policy design rather than technology deployment alone [19]. This implies the need for carbon data authorities, algorithmic audit bodies, interoperability standards, flexibility market regulators, and public mechanisms for reviewing AI-enabled operational decisions. Such institutions should ensure that AI supports net-zero objectives without displacing democratic responsibility for energy policy.

Ethical guardrails and societal acceptance

Ethical guardrails are necessary because carbon-aligned AI orchestration may affect comfort, mobility, industrial schedules, electricity bills, data privacy, and access to flexibility revenues. Justice-oriented clean energy research emphasizes that fairness must be built into transition design rather than added after technical systems are deployed [21]. The model therefore requires transparency, contestability, participatory design, protection against algorithmic discrimination, and safeguards against forms of algorithmic carbon colonialism in which powerful actors externalize digital or carbon burdens onto less powerful regions. Societal acceptance would be expected to depend not only on technical performance, but also on whether affected communities can understand, influence, and challenge orchestration decisions.

Evaluation Strategy for the Conceptual Model

Conceptual validity and system-level coherence

The conceptual validity of the model can be evaluated by examining whether its three pillars capture the core coordination requirements of net-zero energy systems. Socio-technical transition theory supports this criterion because energy transitions involve interactions among technologies, institutions, markets, practices, and political expectations [18]. The model is coherent if carbon intelligence provides actionable carbon signals, grid flexibility provides operational response capacity, and multi-level governance provides legitimacy, accountability, and coordination. It should be assessed as a conceptual architecture rather than as an empirical model with measured performance.

Stakeholder and multi-level governance validation

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Stakeholder validation could examine whether grid operators, regulators, municipalities, aggregators, community groups, industrial users, and climate governance actors recognize the model's categories as meaningful and usable. Multi-level governance literature suggests that energy policy problems often involve coordination, justice, and power across institutional levels, so validation should include actors from more than one governance scale [21]. Workshops, expert panels, regulatory reviews, and participatory design exercises could test whether the proposed orchestration architecture clarifies responsibilities and exposes conflicts. Such validation would not prove the model empirically, but it could strengthen its practical and institutional relevance.

Transferability and scalability

Transferability should be evaluated by asking whether the model can apply to energy systems with different renewable shares, market designs, governance capacities, digital infrastructures, and justice concerns. AI applications for climate change mitigation span electricity systems, buildings, transport, industry, and policy analysis, which suggests that orchestration models must remain adaptable across domains [28]. Scalability also requires attention to the environmental footprint of AI infrastructure, because larger AI systems may impose additional electricity and material demands that conflict with net-zero goals [12]. The model is therefore transferable only if it can be adapted to local institutional conditions while preserving carbon accountability and system-level coordination.

Limitations

Model abstraction and need for quantitative instantiation

The model is intentionally conceptual and does not provide optimization equations, simulation outputs, cost estimates, or measured carbon outcomes. Reviews of AI in sustainable energy show that technical applications are diverse and context-dependent, so conceptual integration cannot substitute for future empirical validation, modelling, or pilot implementation [2]. The model should therefore be interpreted as a design and governance framework that identifies relationships among AI orchestration, carbon intelligence, flexibility, and governance. Future research would need to translate its concepts into testable architectures, operational protocols, and jurisdiction-specific regulatory designs.

Table 6 presents the core design specifications for embedding policy compliance directly into the AI agent's decision-making architecture.

Table 6. Technical Specifications for a Policy-Bound, AI-Orchestrated Energy Coordination System

Architectural Component	Technical Specification	Policy/Governance Constraint	Operational Benefit
Agent Hierarchy	4-Layer structure: Global Strategic, Regional Grid, Site Optimization, Asset-level micro agents.	Bounded authority per layer; escalation protocols for conflict resolution.	Reduces computational complexity; prevents contradictory commands across grid levels.
Memory Mechanism	Hybrid memory: Short-term context, episodic summaries, long-term vector-symbolic graphs.	*Energy-Weighted Optimization*: Prioritizes retention of carbon-impact data over generic telemetry.	Preserves regulatory audit trails while reducing token/energy overhead.
Decision Autonomy	Constrained Decision Process operating over partially observable states.	*Policy-Bound Validation Gates*: Actions require digital twin simulation and risk assessment prior to execution.	Prevents unsafe or non-compliant automated actions (e.g., discharging storage into a saturated grid).

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Data Governance	Federated edge memory with compressed embedding sharing.	Adherence to data sovereignty laws (e.g., EU AI Act, local grid data classification).	Enables low-latency control at the edge while protecting customer privacy.

Rapid Technological and Political Evolution

A second limitation is that AI technologies, energy markets, carbon accounting practices, and climate policy frameworks are changing quickly. Digital technology reviews for net-zero energy futures show that the field is evolving across data systems, automation, forecasting, platforms, and governance applications [1]. Political change may also alter carbon prices, market incentives, international commitments, and public tolerance for automated energy control. The model therefore requires periodic revision as both AI capabilities and net-zero governance landscapes evolve.

Conclusion

This article developed a conceptual model of AI-orchestrated net-zero energy systems organized around Carbon Intelligence, Grid Flexibility, and Multi-Level Governance. The model contributes an integrated way to understand how AI could coordinate energy operations, carbon information, flexible resources, and institutional responsibilities.

The central argument is that net-zero orchestration cannot be reduced to optimization, forecasting, or automation alone. Carbon intelligence gives AI systems a decarbonization orientation, grid flexibility gives them operational agency, and multi-level governance gives them legitimacy, accountability, and public direction.

The four tables provide practical conceptual instruments for system design and governance assessment. They define the model pillars, map carbon intelligence functions to AI techniques, classify flexibility resources by orchestration challenge, and specify the governance architecture needed across local, national, and international levels.

Future work should develop the model through interdisciplinary co-development, regulatory sandboxes, participatory assessment, and carefully governed real-world pilots. Such work can move AI-orchestrated net-zero systems from conceptual architecture toward accountable, carbon-aligned, and socially legitimate implementation.

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Ethics statement

None

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