ORIGINAL RESEARCH **Open access**

From Smart Grids to Cognitive Energy Systems: Learning, Adaptation, and Collective Intelligence in Future Energy Networks

Kim Jae-sung[1*], Park Soo-yeon[1], Lee Min-ho[2]

Abstract

Smart grids have advanced electricity systems by introducing digital monitoring, automation, and coordinated control, yet they largely remain reactive, rule-based, and limited in their ability to manage the complexity of future energy networks. As power systems become increasingly decarbonized, decentralized, multi-agent, and dynamic, a new conceptual foundation is needed for energy systems that can learn from changing conditions, adapt their behavior, and self-organize through distributed intelligence. This article proposes a conceptual framework for cognitive energy systems as the next evolutionary stage beyond conventional smart grids. Drawing on cognitive science, multi-agent learning, complex adaptive systems theory, and energy informatics, the article defines the core capabilities of cognitive energy systems, including learning, adaptation, anticipation, self-organization, and collective intelligence. Rather than presenting empirical results, the study offers a conceptual and architectural contribution that clarifies the distinction between smart grids and genuinely intelligent energy systems. The proposed framework identifies suitable learning paradigms for energy networks, outlines architectures for distributed and collective intelligence, and emphasizes the symbiotic role of humans as participants, supervisors, and co-learners within cognitive energy ecosystems. Three comparative tables illustrate the evolution from traditional grids to smart grids and cognitive energy systems, map learning approaches to energy-system functions, and define collective intelligence architectures for future networks. The article argues that cognitive energy systems are essential for managing the uncertainty, scale, and interdependence of fully decarbonized energy infrastructures. By articulating their foundational capabilities, architectural principles, and research agenda, this framework provides a basis for designing energy systems that are not merely digitally connected or automated, but genuinely adaptive, intelligent, and capable of collective learning.

Keywords Smart grids, Cognitive energy systems, Learning, Adaptation, Collective intelligence, Future energy networks

*Correspondence:
Kim Jae-sung
jaesung.kim@snu.ac.kr
[1] Department of AI for Smart Grids and Battery Energy Storage Systems, College of Engineering, Seoul National University, Seoul, South Korea
[2] Department of Intelligent Power System Optimization, Faculty of Engineering, KAIST, Daejeon, South Korea

Introduction

Smart grids have expanded the operational intelligence of electricity networks by introducing sensing, communication, automation, and data-driven control into infrastructures that were historically centralized and mechanically coordinated. Yet the increasing penetration of distributed generation, microgrids, flexible loads, electric mobility, and prosumer participation means that future energy networks will face uncertainty, decentralization, and interdependence beyond the limits of conventional smart-grid automation [1]. Existing artificial intelligence applications in smart grids often improve

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

forecasting, monitoring, and control, but they still tend to operate as task-specific tools rather than as components of a system-wide cognitive architecture [2]. This limitation becomes more significant as energy systems require not only information processing but also continuous learning, adaptation, and coordinated reasoning under changing conditions.

The concept of cognitive energy systems represents a paradigm shift toward energy networks that could be designed to sense, learn, reason, adapt, and self-organise across distributed physical and digital layers. Early visions of cognitive organic power distribution systems already suggest that future grids may require self-management capabilities rather than merely centralized supervisory control [3]. In this sense, cognitive energy systems can be conceptualised as intelligent socio-technical infrastructures in which local devices, aggregators, operators, and communities participate in distributed cognition. Such systems would not simply execute programmed responses but would update their internal models, negotiate among agents, and support adaptive decisions in real time.

A dedicated conceptual framework is needed because current research remains fragmented across machine learning, reinforcement learning, federated learning, multi-agent systems, resilience engineering, and smart-grid governance. Reviews of machine learning in energy systems show the breadth of available computational techniques, yet they also indicate that technical learning methods are often discussed without a unifying cognitive-system architecture [4]. Similarly, sustainable-energy machine learning research emphasizes prediction, optimization, and decision support, but the broader transition from automation to cognition requires a more explicit conceptual vocabulary [5]. A cognitive framework can therefore integrate dispersed developments into an architectural vision for future energy networks.

This article contributes by defining cognitive energy systems, distinguishing them from traditional and smart grids, and proposing architectural principles based on distributed cognition, continuous learning, adaptation, and collective intelligence. It draws on research in reinforcement learning for energy management [6], decentralized microgrid intelligence [7], federated learning for smart grids [8], and resilience-oriented microgrid design to articulate a coherent framework rather than a technical model. The article proceeds by reviewing background concepts, defining the cognitive-energy-system construct, developing architectural principles, and mapping learning mechanisms to adaptive capabilities. It then prepares the conceptual basis for Part 2, which extends the framework toward collective intelligence, human-cognition symbiosis, governance, validation, and research challenges.

Background

Smart grids: achievements and limitations

Smart grids have achieved important advances by embedding digital monitoring, communication networks, automated control, and distributed resource coordination into electricity systems. The smart-grid literature has shown how microgrids, distributed energy resources, and digital platforms can enhance flexibility, resilience, and local energy coordination [1]. However, these systems often remain limited by predefined control logic, centralized optimization assumptions, and fragmented decision architectures that do not fully account for emergent behaviour across interconnected agents. As energy systems become more decentralized and dynamic, smart grids require a transition from programmed responsiveness toward cognitive capacities that can interpret context and adapt over time.

Cognitive systems and their principles

Cognitive systems are not merely computational systems; they are architectures capable of perception, learning, reasoning, memory, adaptation, and goal-oriented interaction with an environment. The idea of self-management in cognitive organic power distribution systems suggests that future energy networks could incorporate cognitive principles by enabling components to monitor their own states, learn from changing conditions, and coordinate without constant centralized intervention [3]. In energy systems, cognition would involve distributed interpretation of grid conditions, anticipation of operational consequences, and adaptive alignment between local actions and system-level goals. A

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

cognitive energy system should therefore be understood as a socio-technical architecture in which intelligence is distributed across devices, algorithms, institutions, and human actors.

Learning and adaptation in computational systems

Learning and adaptation in energy systems have been developed through machine learning, deep learning, reinforcement learning, and related computational approaches. Reinforcement learning for demand response demonstrates how agents can learn policies through interaction with energy environments rather than relying only on fixed rules [6]. Deep reinforcement learning for microgrid energy management similarly shows how adaptive control can coordinate storage, flexible demand, and distributed supply under changing conditions [9]. These learning paradigms provide the technical substrate for cognitive systems, but they must be integrated into architectures that govern how learning occurs, how adaptation is constrained, and how system goals are revised.

Collective intelligence and self-organisation

Collective intelligence refers to the capacity of many interacting agents to generate coordinated, adaptive, or problem-solving behaviour that exceeds the capability of isolated components. Multi-agent decentralized energy management in microgrids illustrates how local agents can learn and coordinate decisions across distributed assets [7]. Research on renewable energy integration and microgrid trading using multi-agent deep reinforcement learning further suggests that collective decision-making can support market coordination, flexibility, and local autonomy [10]. In cognitive energy systems, self-organisation would emerge when distributed agents exchange information, adapt their actions, and produce coherent system behaviour without relying exclusively on hierarchical commands.

Early proposals for cognitive energy systems

Early proposals for cognitive energy systems remain nascent, but they point toward architectures that combine distributed sensing, intelligent control, adaptive learning, and self-management. The vision of cognitive organic power distribution systems explicitly frames energy networks as systems that could monitor, diagnose, and reconfigure themselves through decentralized intelligence [3]. Broader surveys of artificial intelligence in smart grids show that AI already supports forecasting, optimization, anomaly detection, and energy management, but these functions are usually treated as separate applications rather than as components of a cognitive whole [2]. The cognitive-energy-system concept therefore extends existing smart-grid intelligence by asking how multiple AI capabilities can be architected into a coherent, learning, adaptive, and collective system.

Conceptual Foundation: Defining Cognitive Energy Systems

From automation to autonomy to cognition

The evolution from traditional grids to smart grids and then to cognitive energy systems can be understood as a progression from automation to autonomy and finally to cognition. Traditional grids relied primarily on centralized planning, mechanical control, and operator-led decision-making, while smart grids introduced digital coordination, sensing, and algorithmic support [1]. Autonomy appears when energy components can make limited local decisions, such as optimizing microgrid operations or managing flexible demand through learned control policies [9]. Cognition goes further by enabling the system to interpret context, learn continuously, adapt its decision logic, and support collective intelligence across distributed agents.

Core capabilities of cognitive energy systems

A cognitive energy system should be architected around five core capabilities: sensing, learning, reasoning, adaptation, and self-organisation. Sensing creates the informational basis for cognition by allowing distributed components to observe local and system conditions, while learning enables those components to update models and policies over time [4].

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

Reasoning connects learning outputs to goals, constraints, and operational context, and adaptation allows the system to respond to non-stationary conditions such as demand shifts, renewable variability, and infrastructure disruptions [5]. Self-organisation then allows local decisions to generate coordinated behaviour, especially when multi-agent learning architectures coordinate distributed energy resources [11].

A Comparative perspective: traditional grid, smart grid, cognitive system

The distinction between traditional grids, smart grids, and cognitive energy systems lies not only in technology but in the form of intelligence embedded in the network. Traditional grids primarily express centralized operational intelligence, smart grids add digital and data-driven intelligence, and cognitive energy systems would exhibit distributed, adaptive, and reflective intelligence [2]. This comparative perspective is necessary because cognitive energy systems should not be seen as merely more advanced smart grids but as infrastructures capable of learning from experience, adapting decision rules, and coordinating collective behaviour across human and machine agents [3]. **Table 1** clarifies this evolution by contrasting the attributes that define each stage of energy-system intelligence.

Table 1. Comparative Evolution of Intelligence, Adaptation, and Decision-Making Across Traditional Grids, Smart Grids, and Cognitive Energy Systems

Attribute	Traditional Grid	Smart Grid	Cognitive Energy System
Intelligence type	Centralized operational expertise embedded in planning rules and operator procedures.	Digital intelligence supported by sensors, communication, analytics, and automation.	Distributed cognitive intelligence across devices, agents, operators, and institutions.
Learning	Minimal system learning; improvements occur mainly through engineering upgrades and planning cycles.	Episodic learning through forecasting models, analytics, and periodic optimization updates.	Continuous learning from real-time data, experience, uncertainty, and changing objectives.
Adaptation	Manual or rule-based adjustment after disturbances or demand changes.	Automated response to monitored conditions using predefined control and optimization logic.	Context-aware adaptation in which policies, agent behaviours, and coordination rules evolve over time.
Human role	Human operators act as primary interpreters, controllers, and decision authorities.	Humans supervise automated tools, dashboards, and decision-support systems.	Humans participate in symbiotic cognition as supervisors, value-setters, explainability users, and governance agents.
Decision-making	Hierarchical and centralized, with limited local discretion.	Partly decentralized but often coordinated through centralized platforms or predesigned optimization.	Multi-level, multi-agent, and adaptive, combining local autonomy with system-level coordination.
Resilience	Restoration depends heavily on redundancy, operator intervention, and physical robustness.	Resilience is enhanced through monitoring, automation, and microgrid coordination.	Resilience may emerge from self-diagnosis, learned recovery, distributed reconfiguration, and collective adaptation.

Architectural Principles for Cognitive Energy Networks

Distributed cognition and edge intelligence

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

Cognitive energy networks should be designed around distributed cognition, where intelligence is embedded not only in central control rooms but also at substations, microgrids, buildings, storage systems, vehicles, and prosumer interfaces. Edge intelligence would allow local components to interpret local conditions, learn from immediate feedback, and act within governance constraints before escalating decisions to higher levels [12]. Reinforcement learning in building energy management shows how local environments can become sites of adaptive decision-making rather than passive demand nodes [12]. In a cognitive architecture, these edge agents would function as situated cognitive units that sense, infer, and coordinate with neighbouring agents.

Hierarchical and heterarchical organisation

A cognitive energy system should combine hierarchy and heterarchy rather than choosing between centralized control and full decentralization. Hierarchical structures remain necessary for safety, reliability, legal accountability, and system-wide coordination, while heterarchical structures allow distributed agents to negotiate, adapt, and respond locally to dynamic conditions [13]. Consensus design for heterogeneous energy storage devices illustrates how coordination can be distributed while still maintaining shared operational objectives [13]. This hybrid organisation would enable cognitive energy systems to preserve grid stability while allowing local intelligence to generate flexible and context-sensitive responses.

Continuous learning loops

Continuous learning loops are essential because cognitive energy systems would operate in environments where demand, generation, weather, market signals, infrastructure conditions, and user behaviour change constantly. Multi-agent deep reinforcement learning for distributed energy management suggests that agents can update strategies through repeated interaction with local and market environments [11]. However, continuous learning in critical infrastructure should be constrained by validation, safety boundaries, and human oversight rather than treated as unconstrained algorithmic self-modification. The architectural challenge is therefore to create learning loops that connect sensing, model updating, decision evaluation, explanation, and governance review across multiple timescales.

Learning and Adaptation Mechanisms

Machine learning paradigms for cognitive energy

Cognitive energy systems require a portfolio of learning paradigms rather than a single dominant algorithmic approach. Supervised and deep learning can support forecasting, classification, anomaly detection, and pattern recognition, while reinforcement learning can support adaptive control and sequential decision-making in dynamic environments [4]. Federated learning provides a privacy-preserving mechanism through which distributed energy actors can share model improvements without exposing raw local data [8]. Together, these paradigms would allow cognitive systems to learn from local experience, system-wide patterns, and cross-site knowledge while maintaining operational and governance boundaries.

Adapting to non-stationarity and surprises

Future energy networks will face non-stationarity because renewable generation, consumption patterns, climate risks, market rules, and user behaviours continuously change. Deep reinforcement learning for microgrid management demonstrates the value of adaptive policies in environments where supply, storage, and demand conditions vary over time [9]. Resilience research on microgrids also indicates that adaptive local resources can contribute to recovery and continuity when centralized infrastructures are disrupted. A cognitive energy system would therefore need mechanisms for detecting drift, revising policies, transferring knowledge across contexts, and escalating uncertainty when automated adaptation becomes unsafe.

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

Meta-learning and self-improvement

Beyond task-level learning, cognitive energy systems may require meta-learning capabilities that help the system learn how to learn across devices, contexts, and timescales. Reviews of machine learning for sustainable energy systems suggest that energy AI must increasingly address generalization, transferability, and deployment robustness rather than isolated predictive accuracy [5]. In a cognitive architecture, self-improvement would mean that the system evaluates which learning strategies remain appropriate under changing conditions, when models should be retrained, and when human review is required. **Table 2** maps key learning paradigms to the energy-system functions and adaptive behaviours they could enable.

Table 2. Learning Paradigms and Their Adaptive Functions in Cognitive Energy Systems

Learning Paradigm	Energy System Function	Adaptation Enabled	Example Cognitive Behaviour
Online learning	Real-time load forecasting, renewable output estimation, local flexibility management.	Continuous adjustment to new data streams and short-term operational drift.	A local controller updates its demand expectations as household behaviour changes during extreme weather.
Reinforcement learning	Demand response, storage dispatch, building energy control, microgrid operation.	Policy adaptation through interaction with changing operational environments.	A microgrid agent learns when to charge storage, curtail flexible loads, or import power under uncertain renewable output.
Deep reinforcement learning	High-dimensional control across buildings, microgrids, queues, and distributed assets.	Adaptive decision-making where state spaces are too complex for fixed rules.	A cognitive controller learns coordinated actions across storage, flexible demand, and local generation.
Federated learning	Privacy-preserving forecasting, anomaly detection, cyber-physical monitoring, distributed model updating.	Cross-site learning without centralizing sensitive operational or user data.	Multiple microgrids jointly improve an anomaly-detection model while retaining local data ownership.
Transfer learning	Adaptation of models across buildings, regions, microgrids, or seasonal operating regimes.	Reuse of learned representations when conditions shift or new sites lack extensive historical data.	A demand-response model trained in one district is adapted to another district with different consumption patterns.
Meta-learning	Selection and revision of learning strategies, retraining policies, and adaptation rules.	Higher-order self-improvement in how the system learns, validates, and updates itself.	A cognitive platform identifies that a forecasting model is no longer reliable and switches to a more appropriate learning strategy.
Multi-agent learning	Distributed coordination among prosumers, storage systems, aggregators, and grid operators.	Collective adaptation through interaction among autonomous agents.	Local agents coordinate flexible demand and storage actions to support system balance without a single central command.

Collective Intelligence in Energy Systems

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

Multi-agent cognitive architectures

Collective intelligence in cognitive energy systems would be grounded in multi-agent architectures where distributed entities learn, coordinate, and adapt while remaining embedded in physical grid constraints. Multi-agent attention-based deep reinforcement learning for demand response illustrates how multiple grid-responsive buildings could coordinate decisions while accounting for local conditions and shared system objectives [14]. Smart community energy management further shows how distributed agents may represent households, storage devices, renewable generators, and aggregators within a shared adaptive environment [15]. In a cognitive energy system, these agents would not simply optimize isolated objectives but would participate in collective reasoning about flexibility, reliability, cost, resilience, and sustainability.

Swarm intelligence and stigmergy

Swarm intelligence offers a useful conceptual lens for energy networks because coordinated system behaviour may emerge from many simple local interactions rather than from a single central controller. Collective intelligence for demand flexibility and climate resilience suggests that urban energy systems could benefit from distributed coordination among buildings, users, and infrastructure assets [16]. In cognitive energy systems, stigmergic coordination could occur when local agents respond to shared signals such as congestion, carbon intensity, flexibility scarcity, or resilience warnings. Such mechanisms should be carefully governed, because the same interaction rules that generate beneficial coordination could also amplify local errors into wider instability.

Emergent behaviour and system-level cognition

System-level cognition may emerge when individual agents, local learning processes, communication protocols, and institutional constraints interact to produce coordinated energy-system behaviour. Deep reinforcement learning for smart-grid operations highlights the growing relevance of adaptive decision-making across generation, storage, demand response, and operational control [17]. Distributed optimal generation control in DC microgrids similarly indicates how local learning agents can contribute to coordinated system operation when their decisions are structured by shared objectives and technical constraints [18]. **Table 3** presents collective intelligence as a layered architecture in which individual cognition, coordination mechanisms, and emergent system behaviour are linked to governance responsibilities.

Table 3. Layered Architecture of Collective Intelligence in AI-Enabled Energy Systems with Associated Functions, Mechanisms, and Governance Considerations

Collective Intelligence Layer	Functions	AI/Mechanisms	Governance Considerations
Individual Agent Layer	Local sensing, forecasting, decision-making, learning, and contextual response by devices, buildings, microgrids, storage systems, prosumers, and aggregators.	Edge AI, reinforcement learning, local forecasting models, adaptive controllers, anomaly detectors, and embedded decision rules.	Define operating boundaries, safety limits, explainability duties, data rights, and conditions under which local autonomy must defer to human or system-level authority.
Interaction/Coordination Layer	Information exchange, negotiation, consensus formation, flexibility sharing, local market participation, and	Multi-agent reinforcement learning, consensus algorithms, federated learning, distributed optimization, attention mechanisms, and	Govern communication standards, interoperability, cyber-security, conflict resolution, fairness in coordination, and protection against strategic manipulation.

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

	coordinated response to system signals.	peer-to-peer communication protocols.	
Emergent System Layer	System-wide balancing, resilience, adaptive recovery, collective learning, congestion mitigation, and dynamic alignment between local actions and network-level goals.	Emergent coordination, swarm-like adaptation, collective intelligence, digital twins, system-level monitoring, and meta-learning feedback loops.	Monitor unintended emergence, ensure accountability for distributed decisions, validate system-level behaviour, and preserve human oversight over critical transitions.

Managing stability in collective intelligence

The promise of collective intelligence must be balanced against the risk that interacting agents could create oscillations, coordination failures, or unexpected system behaviour. Distributed load restoration using multi-agent deep reinforcement learning shows how intelligent agents could assist recovery, yet it also underscores the need for careful design when learning systems operate in critical infrastructure [19]. Resilience enhancement through mobile power sources and repair crews further indicates that adaptive coordination can support restoration when physical and digital resources are jointly orchestrated [20]. Cognitive energy systems should therefore include stability safeguards, bounded autonomy, supervisory override mechanisms, and continuous monitoring of emergent behaviour.

Human-Cognition Symbiosis and Governance

The role of humans in cognitive energy systems

Human actors would remain central to cognitive energy systems, not as manual controllers of every action but as participants in a broader cognitive architecture. Operators, prosumers, communities, regulators, and energy service providers would define values, interpret explanations, resolve conflicts, and intervene when automated adaptation reaches uncertainty or accountability limits. Research on hybrid renewable microgrids in residential communities illustrates that local energy systems are socio-technical environments rather than purely technical control problems [21]. Cognitive energy systems should therefore be designed as human-machine collective systems in which machine intelligence expands human situational awareness without displacing democratic control over public infrastructure.

Explainability and trust in cognitive systems

Explainability is essential because a cognitive energy system that learns and adapts continuously could become difficult for operators, regulators, and users to understand. Artificial intelligence applications in renewable energy systems already raise security and interpretability concerns as AI becomes embedded in forecasting, control, and operational decision-making. In cognitive energy systems, explanations should not be limited to model outputs but should clarify why an agent acted, what information it used, how uncertainty was handled, and which governance constraints shaped the decision. Trust would depend on whether humans can interrogate cognitive behaviour during normal operation, stress conditions, and recovery phases.

Ethical and societal implications

The transition from smart grids to cognitive energy systems creates ethical questions about autonomy, accountability, access, privacy, and distributive consequences. Secure federated learning for smart grids suggests one pathway for balancing distributed intelligence with data protection, but privacy-preserving learning alone does not resolve broader governance questions about who benefits from collective intelligence [8]. False data injection detection through federated deep learning further shows that security and trust must be embedded into learning architectures rather than added after

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

deployment [22]. Cognitive energy systems should therefore be governed as public-value infrastructures, not merely as technical platforms for optimization.

Governance frameworks for cognitive energy networks

Governance frameworks for cognitive energy networks should define the rights, responsibilities, and limits of autonomous and semi-autonomous energy agents. Distributed anomaly detection through federated learning indicates that future grid governance will need to coordinate intelligence across many actors while preserving local data boundaries and operational autonomy [23]. Such governance should include standards for model validation, explainability, incident reporting, adaptive control limits, cyber-security, human override, and accountability across distributed decisions. Cognitive energy governance must therefore evolve from regulating assets and markets toward regulating learning processes, agent interactions, and emergent system behaviour. **Figure 1** presents the proposed foundation-model risk governance architecture for cognitive energy systems.

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

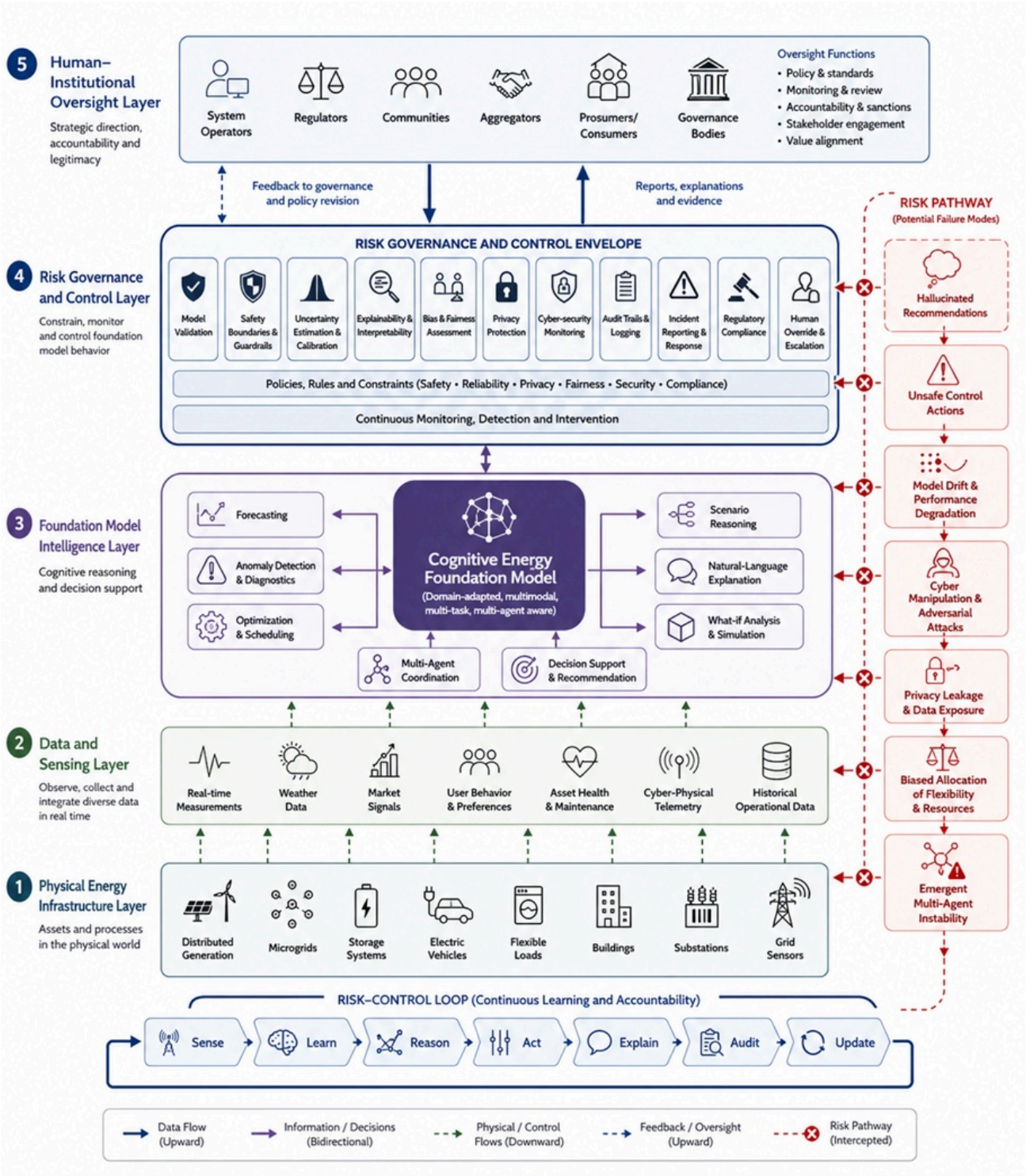

Figure 1. Foundation-Model Risk Governance Architecture for Cognitive Energy Systems

Pathways from Smart Grids to Cognitive Systems

Incremental evolution and pilot projects

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

The transition from smart grids to cognitive energy systems should occur incrementally through controlled pilots, modular architectures, and progressively more sophisticated learning functions. Multi-energy district communities already provide a plausible intermediate setting because they combine buildings, distributed resources, thermal systems, electric loads, and local coordination needs. These environments could be designed to test cognitive functions such as adaptive forecasting, local agent coordination, federated model updating, and human-in-the-loop decision support. Rather than attempting immediate full autonomy, cognitive transition pathways should begin with bounded domains where learning, adaptation, and collective intelligence can be evaluated under governance constraints.

Technological and institutional enablers

Technological enablers of cognitive energy systems include edge computing, interoperable communication protocols, digital twins, distributed AI, federated learning, neuromorphic computing, secure data infrastructures, and explainable decision-support systems. Neuromorphic event-driven semantic communication in microgrids points toward future architectures where energy systems could process information more efficiently and respond to events through brain-inspired computing principles [24]. Institutional enablers are equally important and include regulatory sandboxes, shared governance standards, data trusts, accountability frameworks, and new professional roles linking AI engineering with energy operations. Without institutional adaptation, cognitive technologies may remain fragmented tools rather than components of a coherent energy-system intelligence.

Evaluation, Validation, and Research Challenges

Measuring cognitive performance

Measuring cognitive performance in energy systems would require indicators that go beyond predictive accuracy or operational efficiency. A cognitive system should be evaluated according to its capacity to learn from changing conditions, transfer knowledge across contexts, explain decisions, coordinate agents, recover from disruption, and align adaptation with social and regulatory objectives. Bibliographic analyses of AI and machine learning in energy systems show that the field is expanding rapidly, but they also imply the need for more integrative criteria for assessing system-level intelligence [25]. Cognitive performance should therefore be treated as a multi-dimensional construct linking technical learning, operational resilience, governance quality, and human interpretability.

Simulation and digital twin testbeds

Because cognitive energy systems would involve adaptive and emergent behaviour, validation should rely on simulation environments, digital twins, controlled field pilots, and staged deployment rather than direct uncontrolled experimentation in critical infrastructure. Reviews of renewable-energy AI applications show the diversity of algorithmic approaches now entering energy domains, which increases the need for testbeds that can compare architectures under realistic operational, cyber-physical, and governance conditions. Digital twins could be used conceptually to examine how cognitive agents learn, interact, and adapt before they are allowed to influence real infrastructure. Such validation should focus not on artificial performance claims but on safety, robustness, explainability, governance compliance, and failure containment.

Interdisciplinary research agenda

The research agenda for cognitive energy systems must connect energy engineering, artificial intelligence, cognitive science, complexity theory, cyber-security, governance studies, and social science. Artificial intelligence in renewable energy systems demonstrates the technical promise of AI, while also raising security challenges that require interdisciplinary attention . Energy-system cognition cannot be reduced to algorithms because learning agents operate within markets, communities, infrastructures, regulations, and institutional histories. Future research should therefore examine how cognitive architectures can be designed to learn effectively, adapt safely, coordinate collectively, and remain accountable to human and societal values.

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

Limitations

Speculative nature and long time horizon

This article is conceptual and forward-looking, so its framework should be interpreted as an architectural vision rather than as a validated implementation model. The literature on deep reinforcement learning, federated learning, microgrid resilience, and energy AI provides relevant building blocks, but these building blocks do not yet constitute a fully realised cognitive energy system [17]. The proposed framework therefore identifies design principles and research directions rather than demonstrating feasibility through experiments or field deployment. Its value lies in clarifying what the transition from smart to cognitive energy systems could require.

Complexity and unpredictability of emergence

A second limitation is that collective intelligence and self-organisation are inherently difficult to predict, especially when learning agents interact across physical, digital, economic, and social layers. Multi-agent learning in energy systems suggests substantial promise, but emergent coordination may also create new vulnerabilities when agent incentives, communication delays, model errors, or governance constraints interact unexpectedly [10]. Cognitive energy systems would therefore require humility in design, staged validation, continuous oversight, and mechanisms for interrupting harmful emergent dynamics. The framework should be read as a basis for disciplined research rather than as a claim that cognition automatically improves energy-system performance.

Conclusion

Cognitive energy systems represent a paradigm shift from digitally enhanced smart grids toward energy networks capable of learning, adaptation, reasoning, and collective intelligence. This article has conceptualised such systems as distributed socio-technical architectures in which intelligence emerges across devices, agents, operators, communities, and institutions.

The transformative potential of cognitive energy systems lies in their ability to move beyond fixed automation and toward adaptive coordination under uncertainty. Realising this potential will require new design paradigms that treat learning, governance, explainability, resilience, and human oversight as foundational architectural elements rather than optional additions.

A concerted research effort is now needed to move from conceptual aspiration to responsible design. Future energy networks should not only become smarter but should become capable of disciplined cognition: learning from experience, adapting safely, coordinating collectively, and remaining accountable to the societies they serve.

Acknowledgements

None

Conflict of interest

None

Financial support

None

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

Ethics statement

None

Received: 27 Oct 2023 Revised: 02 Jan 2024 Accepted: 19 Jan 2024
Published online: 15 November 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. Yoldaş Y, Önen A, Muyeen SM, Vasilakos AV, Alan İ. Enhancing smart grid with microgrids: challenges and opportunities. Renew Sustain Energy Rev. 2017;72:205-14. https://doi.org/10.1016/j.rser.2017.01.064.

2. Omitaomu OA, Niu H. Artificial intelligence techniques in smart grid: a survey. Smart Cities. 2021;4(2):548-68. https://doi.org/10.3390/smartcities4020029.

3. Loeser I, Braun M, Gruhl C, Menke JH, Sick B, Tomforde S. The vision of self-management in cognitive organic power distribution systems. Energies. 2022;15(3):881. https://doi.org/10.3390/en15030881.

4. Forootan MM, Larki I, Zahedi R, Ahmadi A. Machine learning and deep learning in energy systems: a review. Sustainability. 2022;14(8):4832. https://doi.org/10.3390/su14084832.

5. 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.

6. Vázquez-Canteli JR, Nagy Z. Reinforcement learning for demand response: a review of algorithms and modeling techniques. Appl Energy. 2019;235:1072-89. https://doi.org/10.1016/j.apenergy.2018.11.002.

7. Kofinas P, Dounis AI, Vouros GA. Fuzzy Q-Learning for multi-agent decentralized energy management in microgrids. Appl Energy. 2018;219:53-67. https://doi.org/10.1016/j.apenergy.2018.03.017.

8. Su Z, Wang Y, Luan TH, Zhang N, Li F, Chen T, et al. Secure and efficient federated learning for smart grid with edge-cloud collaboration. IEEE Trans Ind Inform. 2022;18(2):1333-44. https://doi.org/10.1109/TII.2021.3095506.

9. Nakabi TA, Toivanen P. Deep reinforcement learning for energy management in a microgrid with flexible demand. Sustain Energy Grids Netw. 2021;25:100413. https://doi.org/10.1016/j.segan.2020.100413.

10. Harrold DJB, Cao J, Fan Z. Renewable energy integration and microgrid energy trading using multi-agent deep reinforcement learning. Appl Energy. 2022;318:119151. https://doi.org/10.1016/j.apenergy.2022.119151.

11. Fang X, Zhao Q, Wang J, Han Y, Li Y. Multi-agent deep reinforcement learning for distributed energy management and strategy optimization of microgrid market. Sustain Cities Soc. 2021;74:103163.

12. Mason K, Grijalva S. A review of reinforcement learning for autonomous building energy management. Comput Electr Eng. 2019;78:300-12.

13. Khazaei J, Nguyen DH. Multi-agent consensus design for heterogeneous energy storage devices with droop control in smart grids. IEEE Trans Smart Grid. 2019;10(2):1395-404. https://doi.org/10.1109/TSG.2017.2765241.

14. Xie J, Ajagekar A, You F. Multi-agent attention-based deep reinforcement learning for demand response in grid-responsive buildings. Appl Energy. 2023;342:121162.

15. Wilk P, Wang N, Li J. Multi-agent reinforcement learning for smart community energy management. Energies. 2024;17(20):5211.

16. Nik VM, Moazami A. Using collective intelligence to enhance demand flexibility and climate resilience in urban areas. Appl Energy. 2021;281:116106.

17. Li Y, Yu C, Shahidehpour M, Yang T, Zeng Z, Chai T, et al. Deep reinforcement learning for smart grid operations: algorithms, applications, and prospects. Proc IEEE. 2023;111(9):1055-96.

18. Fan Z, Zhang W, Liu W. Multi-agent deep reinforcement learning-based distributed optimal generation control of DC microgrids. IEEE Trans Smart Grid. 2023;14(5):3337-51.

19. Vu L, Vu T, Vu TL, Srivastava A. Multi-agent deep reinforcement learning for distributed load restoration. IEEE Trans Smart Grid. 2024;15(2):1749-60. https://doi.org/10.1109/TSG.2023.3310893.

20. Wang Y, Qiu D, Teng F, Strbac G. Towards microgrid resilience enhancement via mobile power sources and repair crews: a multi-agent reinforcement learning approach. IEEE Trans Power Syst. 2024;39(1):1329-45. https://doi.org/10.1109/TPWRS.2023.3240479.

21. Kumar NM, Chopra SS, Chand AA, Elavarasan RM, Shafiullah GM. Hybrid renewable energy microgrid for a residential community: a techno-economic and environmental perspective in the context of the SDG7. Sustainability. 2020;12(10):3944. https://doi.org/10.3390/su12103944.

22. Li Y, Wei X, Li Y, Dong Z, Shahidehpour M. Detection of false data injection attacks in smart grid: a secure federated deep learning approach. IEEE Trans Smart Grid. 2022;13(6):4862-72.

23. Jithish J, Alangot B, Mahalingam N, Yeo KS. Distributed anomaly detection in smart grids: a federated learning-based approach. IEEE Access. 2023;11:7157-79.

24. Diao X, Song Y, Sahoo S, Li Y. Neuromorphic event-driven semantic communication in microgrids. IEEE Trans Smart Grid. 2024;15(5):4300-14. https://doi.org/10.1109/TSG.2024.3370822.

25. Entezari A, Aslani A, Zahedi R, Noorollahi Y. Artificial intelligence and machine learning in energy systems: a bibliographic perspective. Energy Strateg Rev. 2023;45:101017. https://doi.org/10.1016/j.esr.2022.101017.

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