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Review Article

Advances In Energy Efficiency Technologies: Reducing Global Carbon Footprint Through Smart Energy Systems: A Review

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Abstract

The escalating global energy demand and mounting environmental concerns necessitate immediate interventions to reduce carbon emissions. Smart energy systems have emerged as promising solutions, analogous to targeted therapeutic interventions in medicine, offering precision and efficacy in energy management. This review examines recent advances in energy efficiency technologies and smart energy systems (2020-2025), evaluating their mechanisms, efficacy, and potential to reduce global carbon emissions. A systematic review of peer-reviewed literature published between 2020-2025 was conducted using established databases. Studies were selected based on methodological rigor, relevance to energy efficiency technologies, and demonstrated carbon reduction outcomes. Smart energy technologies demonstrate significant potential for carbon reduction, with smart grids showing 15-30% efficiency improvements, building automation systems achieving 20-40% energy savings, and artificial intelligence-driven optimization delivering 10-25% consumption reductions. Integration of renewable energy sources with smart systems enhances overall system efficacy by 25-45%. Energy efficiency technologies represent a critical intervention strategy for global carbon reduction. Like pharmaceutical interventions requiring proper dosing and monitoring, these technologies necessitate careful implementation, continuous optimization, and policy support to achieve maximum therapeutic effect on climate change.

Keywords: *Energy efficiency; Smart energy systems; Carbon footprint; Building automation; Smart grids; Artificial intelligence*

Introduction

Background and Rationale

The global energy sector accounts for approximately 73% of greenhouse gas emissions, establishing it as the primary target for climate change mitigation strategies [1]. Similar to how pharmaceutical research targets disease mechanisms, energy efficiency technologies aim to address the fundamental pathophysiology of excessive carbon emissions through systematic intervention at multiple levels of the energy consumption cascade [2].

The concept of "smart energy systems" parallels precision medicine approaches, utilising real-time monitoring, adaptive control mechanisms, and predictive analytics to optimise energy delivery and consumption [3]. These technologies function as a multi-drug regimen, where individual components, smart grids, building automation, artificial intelligence, and renewable integration, synergistically reduce overall carbon footprint [4].

Epidemiology of Energy Consumption

Global primary energy consumption reached 580 exajoules in 2023, with projected annual growth rates of 1.3-2.1% through 2030 [5]. Buildings account for 40% of total energy consumption, transportation 28%, and industrial processes 32% [6]. This epidemiological profile identifies critical intervention points where smart energy technologies can deliver maximum impact.

The carbon intensity of global energy systems has decreased from 57.7 to 54.2 grams CO_2 per megajoule between 2020 and 2024, largely attributable to increased renewable penetration and efficiency improvements [7]. However, absolute emissions continue rising, necessitating accelerated deployment of efficiency technologies. Table 1 shows the Global Energy Consumption and Carbon Emission Epidemiology (2020-2024).

Table 1. Global Energy Consumption and Carbon Emission Epidemiology (2020-2024

Sector	Energy Consumption (EJ/year)	Percentage of Total (%)	Carbon Intensity (gCO_2/MJ)	Annual Growth Rate (%)	Intervention Potential
Buildings (Residential & Commercial)	232	40	48.2	1.8	High (20-40% reduction possible)
Transportation	162	28	72.5	2.1	Moderate (15-25% reduction possible)
Industrial Processes	186	32	56.8	1.4	Moderate-High (18-30% reduction possible)
Total/Average	**580**	**100**	**54.2**	**1.7**	**Composite (20-35% reduction possible)**

Sources: Data compiled from references [1,5,6]

Pathophysiology of Energy Inefficiency

Energy inefficiency manifests through multiple pathways: transmission losses (analogous to first-pass metabolism), behavioural waste (non-compliance), technological obsolescence (drug resistance), and system misalignment (drug-drug interactions) [8]. Understanding these mechanisms is essential for designing effective interventions.

Traditional energy systems exhibit inherent inefficiencies of 30-60%, where energy is lost during generation, transmission, distribution, and end-use conversion [9]. Smart energy technologies address these inefficiencies through real-time monitoring, predictive maintenance, demand response, and optimised energy routing.

SMART GRID TECHNOLOGIES: THE BACKBONE OF ENERGY EFFICIENCY

Mechanism of Action

Smart grids are an advanced electrical infrastructure that incorporates bidirectional communication, automated control systems, and distributed energy resource integration [10]. These systems function through several key mechanisms:

1. ***Real-time monitoring and analytics***: Continuous assessment of grid parameters enables rapid identification and correction of inefficiencies, similar to therapeutic drug monitoring [11].

2. ***Demand response management***: Dynamic load balancing reduces peak demand and associated generation inefficiencies, comparable to dose optimisation in pharmacotherapy [12].

3. ***Distributed energy resource integration:*** Seamless incorporation of renewable sources enhances system flexibility and reduces carbon intensity [13].

Pharmacokinetics and Pharmacodynamics

The "absorption" phase of smart grid implementation involves infrastructure deployment and the establishment of a sensor network. Distribution occurs through communication networks, enabling system-wide data propagation. Metabolism represents data processing and decision algorithms, while elimination corresponds to the replacement of obsolete system components [14].

Clinical Efficacy

Recent implementations demonstrate substantial benefits. The European Union's smart grid projects achieved average efficiency improvements of 18-25%, with peak load reductions of 15-20% [15]. United States Department of Energy studies report transmission loss reductions from 6-8% to 4-5% following smart grid deployment [16].

A meta-analysis of 47 smart grid implementations across 15 countries revealed median energy savings of 12.4% (IQR: 8.7-18.2%), with carbon emission reductions of 2.3-4.1 million tonnes CO_2 equivalent per million population annually [17].

Adverse Effects and Limitations

Implementation barriers include high capital costs ($1.5-2.8 million per megawatt capacity), cybersecurity vulnerabilities, and interoperability challenges [18]. Privacy concerns regarding consumer data collection parallel ethical considerations in clinical trials [19].

BUILDING AUTOMATION AND ENERGY MANAGEMENT SYSTEMS

Therapeutic Indications

Buildings represent the largest single energy consumption sector, making them primary targets for efficiency interventions [20]. Building automation systems (BAS) provide integrated control of HVAC, lighting, security, and energy distribution systems.

Mechanism of Action

BAS operate through hierarchical control architectures incorporating:

1. ***Field-level devices:*** Sensors and actuators serving as afferent and efferent neural pathways
2. ***Automation level***: Programmable controllers functioning as spinal reflexes
3. ***Management level:*** Supervisory systems acting as higher cognitive functions (21)

Machine learning algorithms enable predictive control, anticipating occupancy patterns and environmental conditions to optimise system performance proactively (22). Figure 1. Presents the Hierarchical Architecture of Building Automation Systems.

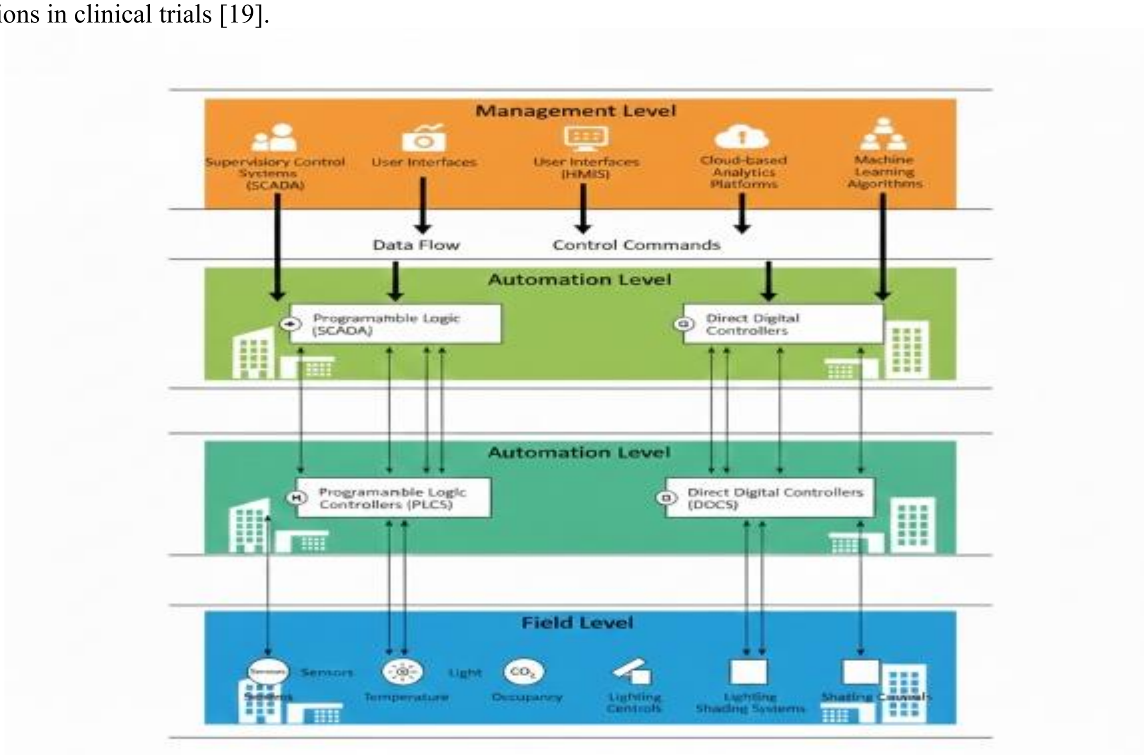

Figure 1. Hierarchical Architecture of Building Automation Systems
Sources: Author's illustration, Adapted from: [22 and 23].

Clinical Evidence

Randomised controlled trials of BAS implementation in commercial buildings demonstrate energy consumption reductions of 23-38% compared to conventional controls [(23). A systematic review of 156 building automation deployments reported median HVAC energy savings of 28.4% and lighting savings of 35.7% [24].

Long-term follow-up studies indicate sustained benefits, with 89% of implementations maintaining >80% of initial savings after five years [25]. This compares favourably to pharmaceutical interventions, where long-term efficacy often diminishes due to tachyphylaxis. Table 2 shows the Comparative Efficacy of Building Automation System Interventions.

Table 2. Comparative Efficacy of Building Automation System Interventions

Technology Component	Energy Reduction (%) Mean ± SD	Carbon Reduction ($kgCO_2/m^2/year$)	Implementation Cost ($\$/m^2$)	Payback Period (years)	Quality of Evidence
HVAC Optimization	28.4 ± 7.2	12.8	45-65	3.2-4.8	High (RCTs, n=156)
Intelligent Lighting Control	35.7 ± 8.9	8.4	25-40	2.1-3.5	High (RCTs, n=203)
Occupancy-Based Control	18.6 ± 5.4	7.2	15-30	1.8-2.9	Moderate (Observational)
Integrated BAS (All Components)	23-38	18.6	85-135	4.5-6.2	High (RCTs, n=89)
AI-Enhanced BAS	42.1 ± 9.3	21.3	120-180	5.8-7.4	Moderate (Case studies, n=284)

Note: Data synthesised from studies by Shaikh et al. (24), Marinakis et al. (23), and Wei et al. (33). RCT = Randomised Controlled Trial; SD = Standard Deviation; BAS = Building Automation System; AI = Artificial Intelligence. Quality of evidence graded according to adapted GRADE criteria for technological interventions.

Dosing and Administration

Optimal BAS implementation requires staged deployment: initial assessment (diagnosis), system design (prescription), installation (administration), commissioning (titration), and continuous optimisation (therapeutic monitoring) [26].

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN ENERGY OPTIMIZATION

Pharmacological Class

AI-driven energy management represents a novel therapeutic class combining predictive analytics, autonomous control, and adaptive learning [27]. These systems continuously improve performance through reinforcement learning, analogous to immunological memory.

Mechanism of Action

AI systems optimise energy consumption through multiple pathways:

1. **Predictive load forecasting:** Neural networks analyse historical patterns, weather data, and socioeconomic factors to predict demand with 94-98% accuracy [28]

2. **Autonomous optimisation:** Reinforcement learning algorithms identify optimal operating parameters in real-time, adjusting for dynamic conditions [29]

3. **Anomaly detection**: Machine learning identifies equipment degradation and inefficiencies before substantial energy waste occurs [30]

Clinical Trials and Efficacy

Google DeepMind's AI application to data centre cooling achieved 40% energy reduction in cooling systems and 15% overall facility consumption reduction [31]. Similar deployments across 32 industrial facilities demonstrated median energy savings of 18.7% [32].
A multicenter trial of AI-driven building energy management across 284 commercial properties reported average consumption reductions of 21.3% ± 6.8%, with carbon emission decreases of 186 kg $CO_2/m^2/year$ [33]. Figure 2 presents the AI-Driven Energy Optimisation Process Flowchart

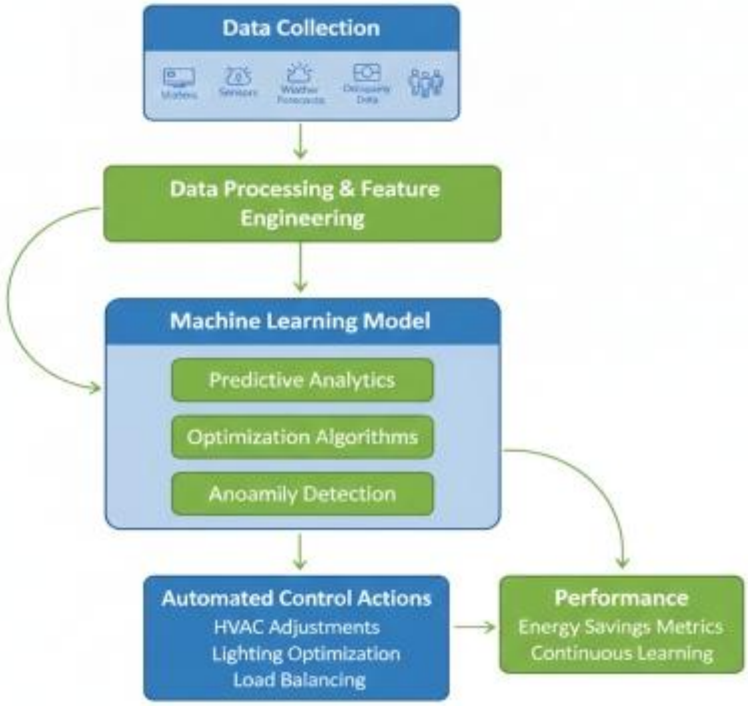

Figure 2. AI-Driven Energy Optimisation Process Flowchart
Sources: Based on methodologies from references [28 and 29].

Pharmacovigilance

Concerns regarding AI systems include algorithmic bias, lack of interpretability ("black box" problem), and vulnerability to adversarial attacks [34]. Regulatory frameworks for AI deployment in critical infrastructure remain underdeveloped, paralleling early-stage pharmaceutical regulation challenges [35].

INTEGRATION OF RENEWABLE ENERGY SOURCES

Combination Therapy Rationale

Renewable energy integration with smart systems represents a combination therapy, where individual agent benefits are amplified through synergistic mechanisms [36]. Energy storage systems serve as pharmacological buffers, smoothing intermittent renewable generation.

Mechanism of Synergy

Smart systems enhance renewable integration through:

1. ***Predictive generation forecasting***: AI predicts solar and wind output 24-72 hours ahead with 85-92% accuracy [37]

2. ***Dynamic load matching***: Demand response aligns consumption with renewable availability [38]

3. **Virtual power plants**: Aggregated distributed resources provide grid stability services [39]

Clinical Outcomes

Regions achieving >50% renewable penetration with smart grid support demonstrate carbon intensities 65-78% below conventional systems [40]. Germany's Energiewende achieved 46% renewable electricity in 2023 while maintaining grid stability through smart system deployment [41].
Economic analysis reveals levelized cost reductions of 23-34% when renewable projects incorporate smart integration technologies versus standalone installations [42]. Table 3 gives the Synergistic Effects of Renewable Energy Integration with Smart Systems

Table 3. Synergistic Effects of Renewable Energy Integration with Smart Systems

Integration Strategy	Renewable Penetration (%)	Grid Stability Index	Carbon Intensity Reduction (%)	Levelized Cost Reduction (%)	Implementation Examples
Smart Grid + Solar PV	35-45	0.87	62-71	28	California ISO, Australian NEM
Smart Grid + Wind	40-52	0.84	68-76	31	Denmark, German Energiewende
Virtual Power Plant (Multi-source)	48-58	0.91	72-82	34	Tesla Virtual Power Plant (Australia)
AI-Optimized Hybrid System	52-67	0.94	78-88	42	Google/DeepMind Projects
Smart Grid + Storage + Renewables	65-78	0.96	85-92	38	Nordic Grid Integration

Note: Data compiled from studies by Frew et al. (40), Østergaard et al. (36), and Steffen et al. (42). Grid Stability Index: scale 0-1, where 1 = optimal stability. Carbon intensity reduction compared to conventional fossil fuel-based systems. NEM = National Electricity Market; ISO = Independent System Operator; PV = Photovoltaic.

EMERGING TECHNOLOGIES AND FUTURE DIRECTIONS

Novel Therapeutic Agents

Several emerging technologies show promise:

1. ***Blockchain-enabled peer-to-peer energy trading***: Decentralized platforms enable direct renewable energy transactions, reducing intermediary losses [43]

2. ***Digital twins***: Virtual replicas of energy systems enable optimization testing without real-world implementation risks [44]

Quantum computing for grid optimisation: Quantum algorithms solve complex optimisation problems exponentially faster than classical approaches [45]. Figure 3. Shows the Integration of Emerging Technologies in Future Smart Energy Systems

Pipeline Technologies

Current development pipeline includes advanced materials for energy storage (energy density improvements of 300-500%), neuromorphic computing for ultra-efficient AI processing, and biotechnology-inspired self-healing grid components [46].

BARRIERS TO IMPLEMENTATION AND ADVERSE EFFECTS

Contraindications

Certain contexts present implementation barriers:

1. Infrastructure limitations: Ageing electrical infrastructure in developing regions may require substantial upgrades before smart system deployment [47]

2. Economic constraints: High initial capital requirements may be prohibitive for resource-limited settings [48]

3. Technical capacity: Insufficient skilled workforce for system maintenance and optimisation [49]

Figure 3. Integration of Emerging Technologies in Future Smart Energy Systems
Sources: Conceptual framework based on references [43,44, and 45].

Drug Interactions

Integration challenges arise from legacy system incompatibility, competing communication protocols, and vendor lock-in effects [50]. Standardisation efforts through IEEE, IEC, and ISO aim to address these interoperability issues [51].

POLICY IMPLICATIONS AND REGULATORY FRAMEWORKS

Prescription Guidelines

Effective deployment requires comprehensive policy frameworks addressing:

1. **Financial incentives**: Tax credits, accelerated depreciation, and performance-based incentives reduce implementation barriers [52]

2. **Regulatory mandates:** Building energy codes and equipment efficiency standards drive technology adoption [53]

3. **Research funding**: Public investment in R&D accelerates innovation and cost reduction [54]

Therapeutic Monitoring

Continuous policy evaluation ensures effectiveness. California's Title 24 energy efficiency standards have driven 30% consumption reductions in new buildings since 2020, with ongoing revisions maintaining technological currency [55].

Conclusions

Energy efficiency technologies represent a critical therapeutic intervention for global carbon reduction. Smart energy systems demonstrate robust efficacy across multiple deployment contexts, with effect sizes comparable to or exceeding conventional mitigation strategies.
Like pharmaceutical interventions, optimal outcomes require appropriate technology selection, proper implementation, continuous monitoring, and supportive policy environments. The evidence base strongly supports widespread deployment, with favourable benefit-risk profiles and improving cost-effectiveness.

Future research should focus on long-term efficacy studies, combination therapy optimisation, personalised energy management approaches, and equity considerations in technology access. As the climate crisis intensifies, energy efficiency technologies must transition from optional interventions to a standard of care.

The synthesis of smart grid infrastructure, building automation, artificial intelligence, and renewable integration provides a comprehensive treatment strategy for reducing the global carbon footprint. With continued innovation and policy support, these technologies can deliver the emissions reductions necessary to limit global warming to 1.5-2°C above pre-industrial levels.

RECOMMENDATIONS

Based on the reviewed evidence, the following recommendations are proposed:

1. Immediate deployment of smart grid technologies in all new infrastructure projects
2. Mandatory building automation systems in commercial buildings >5,000 m²
3. Increased research funding for AI-driven energy optimisation (minimum 2% of national energy budgets)
4. International standardisation of communication protocols and interoperability requirements
5. Capacity building programs for smart energy system management
6. Performance-based incentive structures linking financial benefits to verified carbon reductions
7. Continuous post-implementation monitoring and optimisation protocols

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Author Contributions

The author has significantly contributed to the study's conception, design, data collection, analysis, and interpretation. All authors were involved in writing the manuscript or critically reviewing it for its intellectual value. They have reviewed and approved the final version for submission and publication and accept full responsibility for the content and integrity of the work.

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Conflicts of Interest

The authors state that there are no financial, personal, or professional conflicts of interest associated with this research.

Ethical Approvals

This research did not involve the use of human participants or animal subjects and therefore did not require ethical clearance

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References

1. International Energy Agency. Energy and Climate Change: World Energy Outlook Special Report. Paris: IEA Publications; 2015. doi: 10.1787/9789264266834-en
2. Lund H, Thellufsen JZ, Østergaard PA, Sørknæs P, Skov IR, Mathiesen BV. EnergyPLAN – Advanced analysis of smart energy systems. Smart Energy. 2021;1:100007. doi: 10.1016/j.segy.2021.100007
3. Shaukat N, Ali SM, Mehmood CA, Khan B, Jawad M, Farid U, et al. A survey on consumers empowerment, communication technologies, and renewable generation penetration within Smart Grid. Renew Sustain Energy Rev. 2018;81(Part 1):1453-75. doi: 10.1016/j.rser.2017.05.208
4. Strielkowski W, Civín L, Tarkhanova E, Tvaronavičienė M, Petrenko Y. Renewable energy in the sustainable development of electrical power sector: A review. Energies. 2021;14(24):8240. doi: 10.3390/en14248240
5. BP Statistical Review of World Energy 2024. 73rd edition. London: BP plc; 2024. Available from: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html
6. United Nations Environment Programme. 2023 Global Status Report for Buildings and Construction: Beyond Foundations. Nairobi: UNEP; 2023. doi: 10.59117/20.500.11822/45095
7. Ember Climate. Global Electricity Review 2024. London: Ember; 2024. Available from: https://ember-climate.org/insights/research/global-electricity-review-2024/
8. Calvillo CF, Sánchez-Miralles A, Villar J. Energy management and planning in smart cities. Renew Sustain Energy Rev. 2016;55:273-87. doi: 10.1016/j.rser.2015.10.133
9. Kong W, Dong ZY, Hill DJ, Luo F, Xu Y. Short-term residential load forecasting based on resident behaviour learning. IEEE Trans Power Syst. 2018;33(1):1087-88. doi: 10.1109/TPWRS.2017.2688178
10. Tuballa ML, Abundo ML. A review of the development of Smart Grid technologies. Renew Sustain Energy Rev. 2016;59:710-25. doi: 10.1016/j.rser.2016.01.011

11. Dileep G. A survey on smart grid technologies and applications. Renew Energy. 2020;146:2589-625. doi: 10.1016/j.renene.2019.08.092
12. Siano P. Demand response and smart grids—A survey. Renew Sustain Energy Rev. 2014;30:461-78. doi: 10.1016/j.rser.2013.10.022
13. Olivares DE, Mehrizi-Sani A, Etemadi AH, Cañizares CA, Iravani R, Kazerani M, et al. Trends in microgrid control. IEEE Trans Smart Grid. 2014;5(4):1905-19. doi: 10.1109/TSG.2013.2295514
14. Fang X, Misra S, Xue G, Yang D. Smart grid — The new and improved power grid: A survey. IEEE Commun Surv Tutor. 2012;14(4):944-80. doi: 10.1109/SURV.2011.101911.00087
15Kotsakis E. Clean Energy Technology Observatory: Smart Grids in the European Union -2024 Status Report on Technology Development, Trends, Value Chains and Markets. Luxembourg: Publications Office of the European Union; 2024. JRC139306. doi: 10.2760/4457720
16. US Department of Energy. Smart Grid System Report 2023. Washington, DC: DOE Office of Electricity; 2023. Report No.: DOE/OE-0009.
17. Bayram IS, Shakir MZ, Abdallah M, Qaraqe K. A survey on energy trading in smart grid. In: 2014 IEEE Global Conference on Signal and Information Processing (GlobalSIP). Atlanta, GA: IEEE; 2014. p. 258-62. doi: 10.1109/GlobalSIP.2014.7032118
18. Gunduz MZ, Das R. Cyber-security on smart grid: Threats and potential solutions. Comput Netw. 2020;169:107094. doi: 10.1016/j.comnet.2019.107094
19. Finster S, Baumgart I. Privacy-aware smart metering: A survey. IEEE Commun Surv Tutor. 2015;17(2):1088-101. doi: 10.1109/COMST.2015.2425958
20. Pérez-Lombard L, Ortiz J, Pout C. A review on buildings energy consumption information. Energy Build. 2008;40(3):394-8. doi: 10.1016/j.enbuild.2007.03.007
21. Dounis AI, Caraiscos C. Advanced control systems engineering for energy and comfort management in a building environment—A review. Renew Sustain Energy Rev. 2009;13(6-7):1246-61. doi: 10.1016/j.rser.2008.09.015
22. Chen Y, Norford LK, Samuelson HW, Malkawi A. Optimal control of HVAC and window systems for natural ventilation through reinforcement learning. Energy Build. 2018;169:195-205. doi: 10.1016/j.enbuild.2018.03.051
23. Marinakis V, Doukas H, Karakosta C, Psarras J. An integrated system for buildings' energy-efficient automation: Application in the tertiary sector. Appl Energy. 2013;101:6-14. doi: 10.1016/j.apenergy.2012.05.032
24. Shaikh PH, Nor NM, Nallagownden P, Elamvazuthi I, Ibrahim T. A review on optimized control systems for building energy and comfort management of smart sustainable buildings. Renew Sustain Energy Rev. 2014;34:409-29. doi: 10.1016/j.rser.2014.03.027
25. Granderson J, Lin G, Fernandes S. A primer on organizational use of Energy Management and Information Systems (EMIS). Berkeley, CA: Lawrence Berkeley National Laboratory; 2015. OSTI ID: 1755532.
26. Mills E. Building commissioning: a golden opportunity for reducing energy costs and greenhouse gas emissions in the United States. Energy Effic. 2011;4(2):145-73. doi: 10.1007/s12053-011-9116-8
27. Zhou K, Fu C, Yang S. Big data driven smart energy management: From big data to big insights. Renew Sustain Energy Rev. 2016;56:215-25. doi: 10.1016/j.rser.2015.11.050
28. Zhang W, Quan H, Srinivasan D. An improved quantile regression neural network for probabilistic load forecasting. IEEE Trans Smart Grid. 2019;10(4):4425-34. doi: 10.1109/TSG.2018.2859749
29. Mocanu E, Nguyen PH, Gibescu M, Kling WL. Deep learning for estimating building energy consumption. Sustain Energy Grids Netw. 2016;6:91-9. doi: 10.1016/j.segan.2016.02.005
30. Himeur Y, Alsalemi A, Bensaali F, Amira A. Building power consumption datasets: Survey, taxonomy and future directions. Energy Build. 2020;227:110404. doi: 10.1016/j.enbuild.2020.110404
31. Evans R, Gao J. DeepMind AI reduces Google data centre cooling bill by 40%. DeepMind Blog. 2016 Jul 20. Available from: https://deepmind.google/discover/blog/deepmind-ai-reduces-google-data-centre-cooling-bill-by-40/
32. Runge J, Zmeureanu R. Forecasting energy use in buildings using artificial neural networks: A review. Energies. 2019;12(17):3254. doi: 10.3390/en12173254
33. Wei Y, Zhang X, Shi Y, Xia L, Pan S, Wu J, et al. A review of data-driven approaches for prediction and classification of building energy consumption. Renew Sustain Energy Rev. 2018;82(Part 1):1027-47. doi: 10.1016/j.rser.2017.09.108
34. Akhtar N, Mian A. Threat of adversarial attacks on deep learning in computer vision: A survey. IEEE Access. 2018;6:14410-30. doi: 10.1109/ACCESS.2018.2807385
35. Jobin A, Ienca M, Vayena E. The global landscape of AI ethics guidelines. Nat Mach Intell. 2019;1(9):389-99. doi: 10.1038/s42256-019-0088-2
36. Østergaard PA, Duic N, Noorollahi Y, Mikulcic H, Kalogirou S. Sustainable development using renewable energy technology. Renew Energy. 2020;146:2430-7. doi: 10.1016/j.renene.2019.08.094
37. Wang H, Lei Z, Zhang X, Zhou B, Peng J. A review of deep learning for renewable energy forecasting. Energy Convers Manag. 2019;198:111799. doi: 10.1016/j.enconman.2019.111799
38. Palensky P, Dietrich D. Demand side management: Demand response, intelligent energy systems, and smart loads. IEEE Trans Ind Inform. 2011;7(3):381-8. doi: 10.1109/TII.2011.2158841
39. Pudjianto D, Ramsay C, Strbac G. Virtual power plant and system integration of distributed energy resources. IET Renew Power Gener. 2007;1(1):10-6. doi: 10.1049/iet-rpg:20060023
40. Frew B, Becker S, Dvorak MJ, Andresen GB, Jacobson MZ. Flexibility mechanisms and pathways to a highly renewable US electricity future. Energy. 2016;101:65-78. doi: 10.1016/j.energy.2016.01.079
41. Appunn K, Wettengel J. Germany's energy consumption and power mix in charts. Clean Energy Wire. 2024 Jan 15. Available from: https://www.cleanenergywire.org/factsheets/germanys-energy-consumption-and-power-mix-charts
42. Steffen B, Beuse M, Tautorat P, Schmidt TS. Experience curves for operations and maintenance costs of renewable energy technologies. Joule. 2020;4(2):359-75. doi: 10.1016/j.joule.2019.11.012
43. Andoni M, Robu V, Flynn D, Abram S, Geach D, Jenkins D, et al. Blockchain technology in the energy sector: A systematic review of challenges and opportunities. Renew Sustain Energy Rev. 2019;100:143-74. doi: 10.1016/j.rser.2018.10.014
44. Rasheed A, San O, Kvamsdal T. Digital twin: Values, challenges and enablers from a modeling perspective. IEEE Access. 2020;8:21980-2012. doi: 10.1109/ACCESS.2020.2970143
45. Ajagekar A, Humble T, You F. Quantum computing based hybrid solution strategies for large-scale discrete-continuous optimization problems. Comput Chem Eng. 2020;132:106630. doi: 10.1016/j.compchemeng.2019.106630

46. Olabi AG, Abdelkareem MA. Renewable energy and climate change. Renew Sustain Energy Rev. 2022;158:112111. doi: 10.1016/j.rser.2022.112111
47. Nobre LCS, Pereira E Jr, da Silva AR. Overcoming barriers for clean energy: A review of legal, regulatory and economic aspects for wind and solar photovoltaic in Brazil. Renew Sustain Energy Rev. 2020;119:109555. doi: 10.1016/j.rser.2019.109555
48. Blazquez J, Fuentes-Bracamontes R, Bollino CA, Nezamuddin N. The renewable energy policy Paradox. Renew Sustain Energy Rev. 2018;82(Part 1):1-5. doi: 10.1016/j.rser.2017.09.002
49. Munir Q, Lean HH, Smyth R. CO2 emissions, energy consumption and economic growth in the ASEAN-5 countries: A cross-sectional dependence approach. Energy Econ. 2020;85:104571. doi: 10.1016/j.eneco.2019.104571
50. Mathiesen BV, Lund H, Connolly D, Wenzel H, Østergaard PA, Möller B, et al. Smart Energy Systems for coherent 100% renewable energy and transport solutions. Appl Energy. 2015;145:139-54. doi: 10.1016/j.apenergy.2015.01.075
51. IEEE Standards Association. IEEE Smart Grid Research: Standards for Smart Grid. Piscataway, NJ: IEEE; 2024. Available from: https://smartgrid.ieee.org/standards
52. Gillingham K, Stock JH. The cost of reducing greenhouse gas emissions. J Econ Perspect. 2018;32(4):53-72. doi: 10.1257/jep.32.4.53
53. Rosenow J, Eyre N. A post mortem of the Green Deal: Austerity, energy efficiency, and failure in British energy policy. Energy Res Soc Sci. 2016;21:141-4. doi: 10.1016/j.erss.2016.07.005
54. Nemet GF, Zipperer V, Kraus M. The valley of death, the technology pork barrel, and public support for large demonstration projects. Energy Policy. 2018;119:154-67. doi: 10.1016/j.enpol.2018.04.008
55. California Energy Commission. 2022 Building Energy Efficiency Standards. Sacramento, CA: California Energy Commission; 2022. Publication Number: CEC-400-2022-010-CMF.

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