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Artificial Intelligence for Energy Optimization in Sustainable Manufacturing Systems

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ABSTRACT
Manufacturing accounts for about 28.9% of global final energy use, making inefficient operations a major source of cost and greenhouse gas emissions. This review synthesizes how artificial intelligence supports energy optimization within Industry 4.0-enabled manufacturing systems. It organizes methods into four families: machine learning for forecasting and anomaly detection, deep learning for nonlinear and temporal modelling, reinforcement learning for adaptive scheduling and real-time control, and metaheuristics for balancing energy, throughput, and quality objectives. Applications span plant-level demand prediction and peak management, shop-floor rescheduling under dynamic pricing, equipment-level optimization through predictive maintenance, and system-wide planning using digital twins and cyber-physical integration. Reported benefits include lower energy costs, reduced downtime, improved productivity, and progress toward decarbonization. However, large-scale deployment is constrained by poor data quality and interoperability across IIoT, MES, ERP, and EMS platforms, high implementation and computational costs, skills gaps, and weak governance and benchmarking standards. Emerging solutions include federated learning and edge AI for privacy-preserving, low-latency analytics, explainable AI to enhance trust and auditability, tighter smart-grid integration, and circular economy-driven optimization. The review concludes with practical priorities for reliable, transparent, and scalable AI-enabled energy management.

Keywords: *Energy Optimization, Sustainable Manufacturing, Industry 4.0, Explainable AI, Digital Twins*

Introduction

Manufacturing industries account for a significant share of global energy demand, consuming approximately 28.9% of total final energy worldwide. This high energy intensity is pronounced in energy-intensive sectors such as metal fabrication, chemical production, and electronics manufacturing, contributing not only to operating costs but also to environmental burdens, including greenhouse gas (GHG) emissions. As global industries transition toward net-zero pathways, optimizing energy consumption in manufacturing has become a critical priority to reduce energy use, lower emissions, and enhance economic competitiveness across supply chains (Rolofs et al., 2024; Igbokwe et al., 2025). The drive toward sustainable production has spurred extensive interest in AI-driven energy optimization. Reviews of AI applications in manufacturing highlight substantial opportunities to improve resource efficiency, predictive maintenance, and energy management across diverse sectors. Furthermore, sector-specific analyses demonstrate tangible energy-saving potential in high-energy industries such as cement manufacturing (Oguntola et al., 2024). The integration of digital twins and cyber-physical systems offers a conceptual and practical framework for flexible energy management, enabling real-time optimization and scenario testing that aligns energy performance with production goals (Rolofs et al., 2024). These strands underscore the urgency and value of AI-enabled energy optimization as a core component of sustainable manufacturing transformations (Igbokwe et al., 2025).

Energy efficiency is a cornerstone of sustainable development and industrial competitiveness, underpinned by AI-enabled optimization that can substantially reduce energy intensity in manufacturing and related energy systems (Jun et al., 2022; Hsu et al., 2023), while also supporting broader climate objectives through more efficient operation and planning (Chen et al., 2024; Arévalo et al., 2024). Empirical and review evidence shows that integrating AI with smart grids and energy management not only lowers energy use but also yields direct economic benefits, such as reduced electricity costs in grid-enhanced manufacturing contexts (Chen et al., 2024) and improved alignment with low-carbon development trajectories (Jun et al., 2022; Hsu et al., 2023; Arévalo et al., 2024). Within the Industry 5.0 paradigm, AI-driven, human-centric optimization fosters sustainable and intelligent manufacturing, combining efficiency with customization and resilience to strengthen competitive positioning (Chen et al., 2024). These synergies are evident across sectors, including energy-intensive processes and diversified manufacturing environments, where AI-enabled demand forecasting, optimization, and real-time control contribute to sustained energy performance and resilience under disruptions (Hsu et al., 2023; Arévalo et al., 2024; Safarov, 2024; Oguntola et al., 2024). Thus, energy efficiency transcends regulatory compliance by enabling sustainable value creation and more robust, responsive production systems that support both climate goals and market competitiveness (Jun et al., 2022; Chen et al., 2024; Hsu et al., 2023).

The literature further demonstrates that AI-enabled energy optimization spans planning, operation, and energy-system integration, delivering measurable improvements in sustainability and competitiveness for manufacturing (Hsu et al., 2023; Safarov, 2024; Oguntola et al., 2024). AI-driven dynamic scheduling reduces energy waste and enhances throughput by enabling adaptive resource allocation in the face of variability and disruptions (Nwamekwe et al., 2025) while digital twins coupled with AI provide real-time visibility, predictive maintenance, and energy-performance optimization in manufacturing processes (Safarov, 2024). Smart grids and distributed energy systems, supported by AI-based planning and operation, offer forecasting, optimization, and control capabilities that improve energy efficiency in manufacturing environments (Arévalo et al., 2024; Hsu et al., 2023). The cross-cutting evidence from sectoral studies (including cement manufacturing) and broad reviews confirms that AI-enabled energy management encompassing energy management systems, digital twins, and scheduling can deliver substantial energy savings and advance sustainable operations, reinforcing the link between energy efficiency, resilience, and competitive advantage (Oguntola et al., 2024; Safarov, 2024; Ashok et al., 2023; Chen et al., 2024; Jun et al., 2022; Arévalo et al., 2024). Collectively, these findings position AI as a pivotal enabler of sustainable and cost-effective manufacturing, aligning operational performance with climate imperatives while preserving competitive differentiation through energy-smart processes (Jun et al., 2022; Chen et al., 2024; Hsu et al., 2023; Nwamekwe et al., 2025).

Artificial Intelligence (AI) has emerged as a transformative tool for managing energy demand in manufacturing systems, supported by evidence that AI-enabled approaches can substantially improve energy performance and align operations with climate goals (Jun et al., 2022; Chen et al., 2024; Hsu et al., 2023). AI techniques enable real-time monitoring, adaptive optimization, and predictive modelling that surpass traditional rule-based energy management by leveraging continuous streams of sensor and production data to detect inefficiencies, forecast demand fluctuations, and enhance energy-aware decision-making (Vitalis et al., 2024; Dong et al., 2023). Empirical and review evidence shows that AI-enabled optimization can yield meaningful energy savings across manufacturing contexts, with system-level efficiency gains and broader carbon-reduction potential highlighted in smart-manufacturing and industrial energy studies (Jun et al., 2022; Chen et al., 2024; Hsu et al., 2023). Moreover, integrating AI with the planning and operation of energy systems through digital twins, smart grids, and distributed energy resources enhances both performance and resilience, reinforcing competitive positioning through lower energy intensity and operational costs (Dong et al., 2023; Chen et al., 2024).

The literature clarifies that AI's role spans planning, operation, and energy-system integration, yielding measurable sustainability and competitiveness benefits in manufacturing (Hsu et al., 2023; Jun et al., 2022; Chen et al., 2024). AI-enabled dynamic scheduling reduces energy waste and improves throughput by enabling adaptive resource allocation under variability and disruptions, and is increasingly complemented by AI-powered digital twins that provide real-time visibility and energy-performance optimization in manufacturing processes (Vitalis et al., 2024; Dong et al., 2023). Smart-grid–driven approaches supported by AI offer forecasting, optimization, and load-management capabilities that improve energy efficiency in manufacturing environments and help realize demand-response during peak periods (Hsu et al., 2023; Jun et al., 2022; Chen et al., 2024). In parallel, Industry 5.0 perspectives emphasize human-centric AI integration to balance sustainability with customization and resilience, reinforcing AI's role as a strategic driver of sustainable and cost-effective manufacturing at scale Chen et al., 2024). Collectively, these findings position AI as a pivotal enabler of energy-aware manufacturing that supports climate imperatives while strengthening competitiveness through energy-smart operations (Hsu et al., 2023; Chen et al., 2024; Jun et al., 2022; Chen et al., 2024).

This paper examines the foundations, applications, benefits, challenges, and future directions of AI for energy optimization in manufacturing. It focuses on the integration of AI with Industry 4.0 ecosystems, highlighting predictive forecasting, real-time process control, equipment-level optimization, and supply chain-level applications. The objective is to evaluate AI's role in fostering sustainable and energy-efficient manufacturing systems.

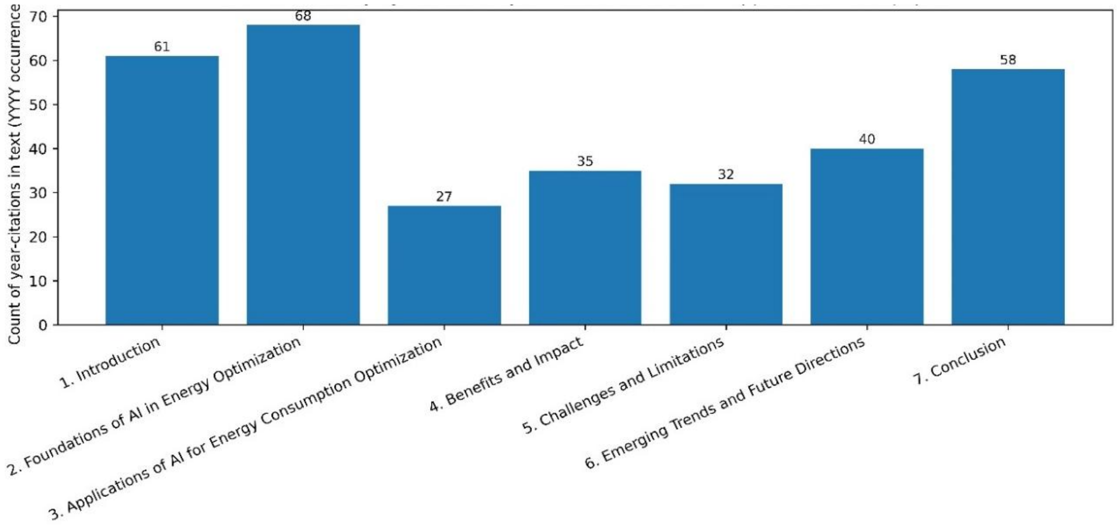

Figure 1: Evidence Density by Section

Figure 1 shows how citations are distributed across Sections 1–7, indicating stronger evidentiary concentration in applications, benefits, and challenges, thereby demonstrating balanced coverage and literature grounding throughout the manuscript structure.

Method

2.1 Overview of AI Techniques

The application of AI in energy optimization encompasses machine learning (ML), deep learning (DL), reinforcement learning (RL), and metaheuristic optimization algorithms, reflecting a broad and integrated toolkit for energy-aware manufacturing. A large body of work demonstrates that AI-enabled optimization improves energy performance by enabling smarter forecasting, control, and planning across smart grids and industrial settings (Chen et al., 2024; Ashok et al., 2023), while broader reviews emphasize the climate and sustainability gains achievable through AI-assisted manufacturing and energy management (Nabati et al., 2022; Jun et al., 2022). In particular, metaheuristic approaches such as genetic algorithms and particle swarm optimization are highlighted for balancing competing objectives production throughput, quality, and energy consumption in multi-objective settings common to sustainable manufacturing (Chen et al., 2024), with additional evidence of AI-driven efficiency gains in energy-intensive sectors such as cement manufacturing (Chen et al., 2024). Collectively, these sources establish AI as a comprehensive instrument for aligning industrial activity with energy and climate objectives while supporting competitive performance (Chen et al., 2024; Ashok et al., 2023; Chen et al., 2024; Jun et al., 2022; Chen et al., 2024).

1. ML models underpin both forecasting and anomaly detection in energy optimization, enabling proactive energy planning and fault identification in manufacturing systems. Systematic reviews and empirical studies show that ML techniques can improve energy efficiency by enhancing demand forecasts, detecting deviations, and supporting anomaly-aware decision-making in production and energy management contexts (Nabati et al., 2022; Ashok et al., 2023; Jun et al., 2022). These capabilities are widely integrated into smart manufacturing and energy-management workflows, where regression- and pattern-learning-based forecasting informs capacity planning and energy allocation, while anomaly detection helps prevent energy waste and equipment faults that would otherwise reduce efficiency (Nabati et al., 2022; Chen et al., 2024; Ashok et al., 2023). The growing convergence of ML with sensor-enabled data streams further strengthens forecasting and monitoring capabilities, reinforcing the role of ML in delivering measurable energy and sustainability benefits across diverse manufacturing domains (Ashok et al., 2023; Chen et al., 2024; Jun et al., 2022). Together, these findings confirm that ML models are foundational for accurate energy forecasting and reliable anomaly detection in AI-driven energy optimization (Nabati et al., 2022; Chen et al., 2024; Jun et al., 2022).
2. DL architectures address nonlinearities and complex temporal patterns in energy demand and supply, supporting more accurate predictions and robust energy-management decisions in manufacturing. Reviews and industry-focused studies document that DL methods are deployed to model nonlinear relationships in energy consumption, process variables, and environmental factors, enabling improved demand prediction and energy-performance optimization within smart-manufacturing ecosystems (Chen et al., 2024; Ashok et al., 2023; Hsu et al., 2023). By harnessing deep feature extraction and sequence modelling, DL facilitates capturing intricate dependencies in energy data that traditional linear models may miss, supporting more reliable planning and control under uncertainty and variability typical of sustainable manufacturing operations (Chen et al., 2024; Dong et al., 2023). The integration of DL with AI-driven planning and control thus reinforces energy efficiency and resilience, contributing to lower energy intensity and stronger competitive positioning (Hsu et al., 2023; Dong et al., 2023; Ashok et al., 2023).

3. RL algorithms enable dynamic, data-driven decision-making in adaptive process control and energy management, addressing the need for real-time optimization under changing conditions. Within smart manufacturing and energy systems, RL has been explored as a mechanism to optimize scheduling, control policies, and energy-aware decisions in the presence of disturbances and demand fluctuations (Dong et al., 2023; Chen et al., 2024). RL's capacity to learn sequential policies from interaction with the environment supports adaptive load balancing, demand response, and online optimization that continuously tune energy use while maintaining throughput and quality (Hsu et al., 2023; Dong et al., 2023). The broader Industry 5.0 and smart-grid literature further situate RL as a central tool for balancing competing objectives energy consumption, productivity, and emissions through human-centric, autonomous decision-making frameworks (Chen et al., 2024; Hsu et al., 2023).
4. Metaheuristic Optimization algorithms such as genetic algorithms (GA) and particle swarm optimization (PSO) are instrumental in balancing trade-offs between production performance and energy consumption, particularly in multi-objective and constraint-rich manufacturing environments. Sustainability-focused reviews highlight GA and PSO as effective search strategies for exploring Pareto-optimal solutions that trade off energy use, cost, and throughput, enabling practitioners to select operating points aligned with strategic goals (Chen et al., 2024). Concrete applications in energy-intensive sectors demonstrate the practical value of AI-driven optimization in reducing electrical energy consumption and improving overall energy efficiency (Chen et al., 2024), underscoring the relevance of metaheuristics for achieving sustainable and competitive manufacturing outcomes (Chen et al., 2024; Chen et al., 2024). The convergence of these optimization approaches with ML/DL/RL paradigms provides a versatile toolkit for coordinating complex production-energy co-optimization in modern sustainable manufacturing systems (Ashok et al., 2023; Chen et al., 2024).

Table 1: AI Techniques and Their Energy-Optimization Roles

AI approach	**Primary energy-optimization role in the manuscript**	**Where it appears (sections)**
Machine Learning (ML)	Predictive energy demand forecasting; anomaly detection;	2.1, 3.1, 3.2 (ML forecasting & anomaly detection; scheduling)

Deep Learning (DL)	Nonlinear + temporal pattern modelling for more accurate	2.1 (DL for nonlinearities/temporal patterns)
Reinforcement Learning (RL)	Adaptive real-time control and energy-aware scheduling u	2.1, 3.2 (RL adaptive control/scheduling)
Metaheuristics (GA/PSO)	Multi-objective optimization: trade-offs among energy use	2.1 (GA/PSO multi-objective)

Table 1 maps ML, DL, RL, and metaheuristics to forecasting, anomaly detection, adaptive control, and multi-objective optimization roles, clarifying how each AI paradigm supports energy efficiency within the manuscript's framework.

2.2 Data Requirements

Effective AI deployment depends on access to high-quality, diverse datasets. Key sources include:

1. IoT-enabled sensor networks capturing equipment-level consumption provide the foundation for fine-grained energy visibility on the shop floor. Embedding sensors on critical assets (motors, drives, compressors, and other energy-intensive equipment) yields equipment-level power measurements, enabling precise tracking of where energy is consumed and where inefficiencies originate. The industrial IoT literature demonstrates that such granular data streams are essential for energy-aware decision-making, anomaly detection, and early fault detection in manufacturing settings (Wójcicki et al., 2022; Chidiebube et al., 2025; Okpala et al., 2024).
2. Smart meters tracking facility-wide demand and load profiles are required to quantify total energy use, identify peak periods, and support demand-side management and peak-shaving strategies. Facility-scale metering complements equipment-level sensors by delivering holistic load profiles and enabling AI-driven optimization of energy procurement, consumption scheduling, and demand response, as highlighted in surveys and reviews of IIoT-enabled energy management and smart manufacturing ecosystems (Chidiebube et al., 2025; Okeagu et al., 2024; Segun-Falade et al., 2024).
3. Production logs documenting machine utilization and throughput are key for linking energy use to production performance. Production data from MES/ERP systems capturing utilization rates, cycle times, and throughput inform capacity planning, energy forecasting, and utilization-aware optimization, as shown in studies that integrate IoT with production

analytics and energy management in smart manufacturing contexts (Okpala et al., 2024; Okeagu et al., 2024).

The fusion of these data sources enables holistic visibility across multiple layers of manufacturing systems. Integrating equipment-level consumption data, facility-wide demand signals, and production-log metrics creates end-to-end analytics capabilities that support cross-layer optimization from individual asset energy performance to plant-wide energy strategies and production scheduling, an approach well documented in AI-enabled energy management studies of Industry 4.0 environments (Okpala et al., 2024; Segun-Falade et al., 2024).

2.3 Integration with Industry 4.0 and Smart Manufacturing

The synergy between AI and Industry 4.0 is central to energy optimization, underpinned by cyber-physical systems, digital twins, and distributed AI-enabled control architectures that provide the computational backbone for embedding AI into manufacturing processes (Nwamekwe et al., 2024; Vyskočil et al., 2023). Digital twins are widely recognized as core enablers in Industry 4.0, delivering real-time visualization, simulation, and optimization of energy flows when coupled with AI analytics (Nwamekwe et al., 2024; Methuselah, 2024). The integration of cyber-physical systems with digital twins and AI-enabled distributed control supports cross-domain data fusion and coordinated energy management across networked plants, as demonstrated by AI-powered on-the-fly replanning in distributed manufacturing execution systems (Vyskočil et al., 2023), and is framed by sustainability-focused Industry 4.0 literature that links digitalization to energy efficiency gains (Nwamekwe et al., 2025; Hsu et al., 2023). Collectively, these capabilities establish a foundation for real-time decision-making and adaptable energy optimization strategies that scale across multi-plant networks (Hsu et al., 2023; Nwamekwe et al., 2024).

Across Industry 4.0 and smart manufacturing, the integration of AI with cyber-physical systems and digital twins enhances real-time decision-making and cross-layer optimization by enabling continuous data exchange among equipment, lines, and facilities through IoT-enabled ecosystems and distributed analytics (Hsu et al., 2023; Nwamekwe et al., 2024). Digital twins provide energy-performance visibility and enable predictive maintenance, allowing proactive adjustments to energy use and load profiles based on simulated and forecasted conditions (Methuselah, 2024). The convergence of AI, digital twins, and smart grids within Industry 4.0 underpins adaptive energy management, demand forecasting, and energy-consumption optimization across distributed manufacturing networks, as reflected in comprehensive reviews of AI applications in smart manufacturing and energy systems (Hsu et al., 2023; Molokwu et al, 2023). This integrated framework positions Industry 4.0 as a scalable platform for sustainable manufacturing, where

AI-driven optimization can continuously learn from operations to improve energy efficiency and competitive performance (Nwamekwe et al., 2025; Hsu et al., 2023).

Results and Discussion

3. Applications of AI for Energy Consumption Optimization

3.1 Predictive Energy Demand Forecasting

Machine learning models enable accurate load forecasting by analysing production schedules, historical consumption, and environmental variables.

1. Short-term forecasting assists in peak load management within daily or weekly horizons by enabling proactive demand response and the scheduling of energy-intensive operations to off-peak periods. AI-driven forecasts leverage sensor data from IoT-enabled equipment networks and facility-wide signals from smart meters to capture near-term fluctuations in energy use and production activity, supporting rapid adjustment of loads and energy procurement strategies (Rojek et al., 2024; Nwamekwe and Chikwendu, 2025). This capability underpins peak shaving and real-time balancing across distributed manufacturing networks, with digital twins and edge-analytic architectures providing rapid recalibration as conditions evolve on the shop floor and in adjacent energy systems (Nwamekwe and Chikwendu, 2025). Collectively, these studies demonstrate how short-horizon predictions translate into tangible reductions in peak demand and improved operational flexibility in modern manufacturing environments (Rojek et al., 2024; Nwamekwe and Chikwendu, 2025).
2. Long-term forecasting supports capacity planning, equipment upgrades, and renewable energy integration by projecting energy requirements and supply opportunities over months to years. AI-enabled predictive analytics inform capital allocation and asset lifecycle decisions by linking expected energy needs with planned productivity targets, equipment modernization, and potential energy-portfolio adjustments to sustain growth while meeting sustainability targets (Olatunde et al., 2024). The integration of digital twins with long-horizon scenario analysis and energy-system planning enables evaluation of trade-offs and resilience across multi-plant networks, helping firms align investment with anticipated demand trajectories and decarbonization goals (Olatunde et al., 2024). These capabilities collectively position AI-powered predictive forecasting as a cornerstone of strategic energy management in sustainable manufacturing (Olatunde et al., 2024).

3.2 Real-Time Process Control and Scheduling

AI enhances process scheduling by dynamically adjusting operations to avoid energy peaks and respond to demand variability and energy pricing in real time

(Nwamekwe et al., 2025). Short-term forecasting supports peak-load management by enabling proactive demand response and scheduling of energy-intensive tasks during off-peak periods. Cross-domain AI applications in smart grids and manufacturing demonstrate the translation of such forecasts into reduced peak demand and improved operational flexibility (Hsu et al., 2023). The computational backbone for these capabilities includes cyber-physical systems, digital twins, and edge-enabled architectures that enable on-the-fly replanning and rapid recalibration of production sequences to mitigate plant-wide energy draw (Vyskočil et al., 2023). Sustainability-focused literature highlights the link between digitalization and energy-efficiency gains across distributed networks (Nwamekwe et al., 2025).

Reinforcement learning (RL)–based adaptive control systems can continuously learn from plant operations to optimize production sequences, ensuring energy use aligns with demand variability and pricing signals. RL-enabled control policies address disturbances and price fluctuations by dynamically reordering or scheduling tasks to minimize energy intensity while maintaining throughput and quality (Nwamekwe et al., 2025). These approaches are increasingly relevant in Industry 5.0 contexts that emphasize human-centric AI and autonomous learning (Chen et al., 2024). The practical realization of RL in production settings is supported by digital twins and CPS integration, which provide safe simulation environments and real-time feedback for policy updates without disrupting operations (Vyskočil et al., 2023). Reviews of AI-driven energy optimization in smart manufacturing confirm RL's value for enhancing adaptive energy management across distributed networks (Hsu et al., 2023; Nwamekwe et al., 2025).

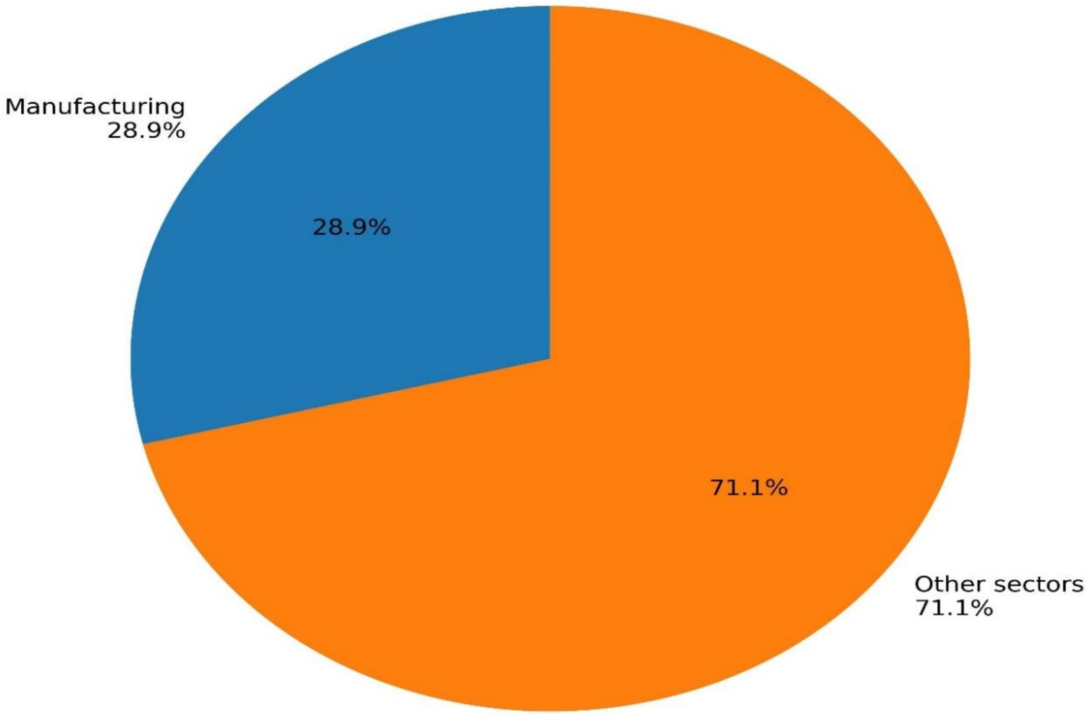

Figure 2: Global Final Energy Use Share

Figure 2 illustrates manufacturing's 28.9% share of global final energy consumption relative to other sectors, visually reinforcing the urgency of AI-driven optimization to reduce industrial energy intensity and emissions.

3.3 Equipment-Level Energy Optimization

At the equipment level, predictive maintenance powered by AI minimizes energy waste by pre-empting failures that lead to inefficiencies. AI-driven predictive maintenance forecasts faults and component degradation before they cause suboptimal operation, enabling planned interventions that avoid energy-intensive downtime and degraded performance. By reducing unplanned outages and transient inefficiencies, energy consumption trajectories on critical assets are stabilized, contributing to lower energy intensity across the asset lifecycle.

AI models also optimize auxiliary systems such as HVAC, air compressors, and machine tools, which often represent significant contributors to non-productive energy use. AI-enabled control and monitoring can tailor HVAC operation to real-time thermal loads and occupancy, optimize compressor sequencing and pressure settings, and reduce idle energy in machine tools through energy-aware scheduling and parameter tuning. The cross-cutting Industry 4.0 paradigm, with digital twins and cyber-physical systems, enables cross-layer energy optimization by providing real-time visibility and safe simulation environments for optimizing energy use across equipment and facilities (Wang et al., 2024; Ezeogidi et al, 2020).

3.4 Production Planning and Supply Chain Integration

AI-driven production planning models enable multi-objective optimization by balancing throughput and energy consumption in modern manufacturing systems. This capability is reinforced by the implementation of digital twins (DT), which facilitate the exploration of alternative schedules under varying demand and energy price signals (Igbokwe et al., 2024). Digital twins simulate diverse production scenarios, allowing managers to evaluate trade-offs between efficiency, costs, and sustainability outcomes, thus selecting operating points that optimally align with corporate energy and carbon goals (Igbokwe et al., 2024). Furthermore, AI-enhanced optimization extends into supply chain integration by coordinating material flows, inventories, and transportation to minimize the cumulative energy footprint across the value chain, leveraging cross-domain DT analytics and cyber-physical systems (CPS) for coordination across plants and warehouses (Nwamekwe et al., 2020; Rolofs et al., 2024).

The integration of production planning with supply chain dynamics through DTs and CPS supports end-to-end energy-aware decision-making, facilitating real-time re-planning and cross-layer optimization as energy costs, demand, and supply conditions evolve (Rolofs et al., 2024). Digital twins provide a shared virtual platform for assessing the energy implications of production and logistics strategies, including on-demand capacity adjustments, batch sizing, and networked scheduling that adhere to sustainability constraints while maintaining throughput (Igbokwe et al., 2024; Nwamekwe et al., 2020). By linking plant-level optimization with inter-plant and supplier interactions, AI-enabled planning can achieve significant energy savings across distributed manufacturing networks while maintaining competitiveness and service levels (Nwamekwe et al., 2020; Rolofs et al., 2024).

4. Benefits and Impact

4.1 Reduction in Operational Costs

Optimized energy consumption lowers direct operating costs by reducing energy bills and curbing energy waste across manufacturing operations, a conclusion supported by reviews on energy management that document substantial efficiency gains in production environments (Rojek et al., 2024; Okpala et al., 2025). By enabling predictive maintenance, anomaly detection, and demand forecasting, AI reduces energy waste from unexpected downtime and suboptimal equipment performance, contributing to lower overall energy expenditures and improved cost visibility (Rojek et al., 2024; Okpala et al., 2025). Furthermore, AI-enabled approaches to microgrid operation and energy-market integration assist firms in mitigating volatile electricity prices, enhancing cost stability and reducing exposure to price spikes in energy markets (Arévalo et al., 2024; Rojek et al., 2024).

Beyond on-site savings, AI facilitates end-to-end cost reductions through cross-domain optimization that links production planning with energy procurement and supply-chain logistics. Digital twins and cyber-physical systems (CPS)-enabled analytics support end-to-end visibility and scenario evaluation, allowing for energy-aware decisions that maintain throughput while minimizing energy use and associated costs (Onyeka et al., 2024). Moreover, integrating AI into supply chains coordinates material flows and transportation to minimize the cumulative energy footprint across the value chain, leading to significant reductions in total cost of ownership and improving resilience to fluctuations in energy markets (Onyeka et al., 2024; Okpala et al., 2025). Collectively, these AI-enabled capabilities translate into sustained operational savings and enhanced competitiveness in sustainable manufacturing contexts (Rojek et al., 2024; Arévalo et al., 2024; Onyeka et al., 2024; Rojek et al., 2024; Okpala et al., 2025).

4.2 Contribution to Sustainability and Decarbonization Goals

AI-enabled systems drive measurable reductions in greenhouse gas (GHG) emissions by improving energy efficiency, enabling renewable energy integration, and curbing wasteful energy consumption across manufacturing and energy platforms (Rojek et al., 2024). In particular, AI-based energy management supports demand forecasting and optimized energy use, yielding tangible efficiency gains and associated emissions reductions in production environments (Rojek et al., 2024). Carbon-footprint reduction frameworks like Sustain AI demonstrate how multi-modal deep learning can further lower industrial emissions. The deployment of AI in microgrid operations and energy-market optimization also enhances the reliability and economics of renewable integration, contributing to a lower overall carbon intensity of the production system (Chen et al., 2024). Beyond plant boundaries, Industry 5.0-oriented optimization promotes sustainable and human-centric pathways that balance productivity with decarbonization objectives (Chen et al., 2024).

The sustainability impact of AI extends into circularity and supply-chain decarbonization, where AI-enabled planning and analytics coordinate material flows to minimize energy footprints across the value chain (Lodhi, 2025). Circular manufacturing perspectives emphasize AI-driven predictive maintenance, process optimization, and resource recovery as levers to reduce energy demand and waste generation, thereby supporting a zero-waste or low-carbon trajectory (Lodhi, 2025). Moreover, AI-supported decision frameworks in Industry 5.0 contexts enable end-to-end energy-aware planning that aligns production schedules, procurement, and logistics with decarbonization goals, while sustaining throughput and service levels (Chen et al., 2024; Lodhi, 2025). Collectively, these trajectories illustrate that AI-based energy optimization is a pivotal enabler of sustainability and decarbonization in modern manufacturing and associated energy systems (Rojek et al., 2024; Lodhi, 2025).

4.3 Enhanced Productivity and Efficiency

Beyond reductions in cost and emissions, AI-enabled energy optimization enhances overall productivity by synchronizing energy efficiency with throughput. It enables energy-aware production planning that minimizes downtime and sustains high output. AI-driven predictive maintenance forecasts faults and component degradation before they cause suboptimal operation, enabling planned interventions that reduce unplanned downtime and energy waste while extending equipment lifecycles (Çınar et al., 2020; Nwamekwe et al., 2025). In parallel, AI-based scheduling and control underpinned by reinforcement learning and online optimization dynamically reorder tasks and adjust process sequences to align energy demand with production needs and energy-price signals, thereby maintaining or increasing throughput while lowering energy intensity (Wang et al., 2024). The integration of digital twins and cyber-physical systems further supports rapid replanning and tight feedback between shop-floor actions and energy performance, contributing to sustained productivity gains without compromising reliability (Wang et al., 2024; Mawson and Hughes, 2020). Collectively, these capabilities illustrate how AI-driven energy optimization translates into measurable gains in productivity and asset utilization across modern manufacturing environments (Çınar et al., 2020; Wang et al., 2024).

The productivity benefits from AI extend into enhanced efficiency through energy-aware design of machining and processing workflows, improved machine-tool energy forecasting, and smarter HVAC and auxiliary-system management that reduces idle and peak-energy episodes without sacrificing throughput (Mawson and Hughes, 2020). For example, energy-prediction models for CNC milling and tool-path optimization can shorten cycle times while cutting energy per part, and integrated planning can ensure optimal utilization of scarce energy resources across the production network. Additionally, AI-enabled maintenance and monitoring support longer asset lifespans and more consistent performance, further boosting long-term productivity by reducing variability in energy consumption and process outcomes (Çınar et al., 2020; Nwamekwe et al., 2025; Mawson and Hughes, 2020). These converging lines of evidence demonstrate that AI-driven energy optimization yields compounded gains in efficiency and throughput, reinforcing competitive advantage in sustainable manufacturing.

5. Challenges and Limitations

5.1 Data Quality, Availability, and Interoperability

Data gaps, inconsistent formats, and lack of interoperability across equipment, manufacturing execution systems (MES), energy management platforms, and enterprise resource planning (ERP) systems pose significant barriers to AI adoption for energy optimization in sustainable manufacturing (Lăzăroiu et al., 2022; Hsu et al., 2023), (Rojek et al., 2024). The industrial data landscape is characterized by heterogeneous sources from IIoT sensors, smart meters, and enterprise applications, which creates uneven data coverage and varying data quality that hinder reliable AI training, validation, and deployment (Lăzăroiu et al., 2022; Okorocha et al., 2022; Rojek et al., 2024). Interoperability challenges across legacy assets and modern AI-enabled systems impede cross-layer analytics and coordinated optimization across distributed manufacturing networks, limiting the effectiveness of end-to-end energy management strategies (Hsu et al., 2023; Rojek et al., 2024). These data-related barriers are echoed in discussions of cognitive manufacturing and smart-grid integrated manufacturing, where data governance and data fusion are identified as critical prerequisites for realizing AI-enabled energy efficiency (Lăzăroiu et al., 2022; Hsu et al., 2023; Rojek et al., 2024).

Overcoming these barriers requires robust data governance, standardization, and interoperability frameworks that align data models, semantics, and interfaces across plants and supply chains (Lăzăroiu et al., 2022; Hsu et al., 2023; Rojek et al., 2024). The integration of digital twins and cyber-physical systems with AI hinges on consistent data streams and interoperable data exchange protocols; standardized interfaces and common data platforms can enable safe, real-time analytics across equipment, lines, and facilities (Hsu et al., 2023; Rojek et al., 2024). Moreover, distributed databases and cross-domain data platforms are essential for end-to-end visibility, enabling scenario analysis and cross-plant optimization that respect sustainability objectives while maintaining performance (Godfrey et al., 2024). Collectively, these pathways data governance, standardized interoperability, and digital-twin driven data fusion are central to unlocking scalable AI-enabled energy optimization in Industry 4.0 style manufacturing ecosystems (Lăzăroiu et al., 2022; Hsu et al., 2023).

5.2 High Implementation Costs and Computational Needs

Initial investments in IoT infrastructure, AI platforms, and computational resources can be prohibitive for many small- and medium-sized enterprises (SMEs), limiting the diffusion of AI-enabled energy optimization in sustainable manufacturing. Beyond the upfront hardware and software licenses, ongoing costs for data storage, cybersecurity, model maintenance, and cloud or edge computing further elevate total ownership expenses, creating a persistent barrier to widespread adoption in resource-constrained firms. The economic hurdles are not only capital-intensive but also encompass regulatory and risk-management considerations inherent to AI-based energy systems, which compound the financial burden for distributed manufacturing contexts (Arévalo et al., 2024).

These cost pressures tend to skew adoption toward larger organizations with deeper capital reserves, potentially exacerbating productivity and sustainability gaps between SMEs and larger incumbents (Arévalo et al., 2024). To realize scalable benefits, SMEs may pursue phased rollouts, shared platforms, or managed-services arrangements; however, these strategies introduce their own governance, integration, and data-sharing costs that must be carefully weighed against anticipated energy savings (Arévalo et al., 2024). Collectively, the literature indicates that while AI offers substantial efficacy for energy optimization, its economic viability hinges on developing low-friction deployment models, accessible tooling, and funding mechanisms that mitigate upfront and ongoing expenditures for SMEs (Arévalo et al., 2024).

5.3 Resistance to Adoption and Skills Gap

Cultural resistance, limited awareness, and a shortage of skilled professionals hinder organizational readiness for AI-driven energy optimization. Insights from engineering-management scholarship emphasize how managerial, regulatory, and organizational factors shape AI adoption, highlighting the need for governance, strategy alignment, and change management to overcome inertia (Akinsolu, 2023). In addition, recent work on Industry 5.0 stresses that trust-building between humans and AI systems is critical, as reluctance to rely on autonomous decisions can slow deployment and undermine perceived reliability (Żywiołek, 2024). The same literature also underscores the importance of workforce capabilities, noting that the successful integration of AI in flexible manufacturing requires skilled personnel who can design, operate, and maintain AI-enabled systems (Nwamekwe and Nwabunwanne, 2025).

To address these barriers, organizations should invest in leadership commitment and structured change-management programs that embed AI adoption into strategic planning, along with targeted upskilling and cross-functional teams to bridge knowledge gaps (Akinsolu, 2023; Nwamekwe and Nwabunwanne, 2025). Building trust through transparent AI workflows, explainable decision-making, and user involvement in the design and validation of AI tools can mitigate cultural resistance and foster user acceptance (Żywiołek, 2024). Collaboration with external partners, universities, vendors, and industry consortia can provide accelerated access to domain expertise and training resources while ensuring governance and data integration standards are in place. Collectively, these approaches help translate AI-driven energy optimization from pilots into scalable, organization-wide capabilities by aligning people, processes, and technology with sustainability objectives (Akinsolu, 2023; Żywiołek, 2024; Nwamekwe and Nwabunwanne, 2025).

5.4 Lack of Standardized Frameworks

The absence of standardized benchmarks and deployment frameworks for AI-driven energy optimization reduces comparability and trust across industrial sectors, hindering cross-site benchmarking and industry-wide adoption. Without agreed-upon metrics for performance, safety, and governance, organizations struggle to validate results, assess risk, and ensure compliance when integrating AI into energy systems on the shop floor and in wider energy networks. This lack of standardization also complicates auditability and accountability, which are increasingly seen as essential for scaling AI in Industry 4.0 and Industry 5.0 contexts while emphasizing human-centric, auditable AI as a prerequisite for widespread deployment.

To address these gaps, concerted efforts are needed to develop interoperable data models, reference architectures, and benchmarking protocols that span equipment, manufacturing execution systems (MES), energy management systems (EMS), and energy networks. Establishing certification schemes, governance guidelines, and standardized risk-management practices would enhance comparability, facilitate cross-sector learning, and improve regulatory acceptance of AI-enabled energy optimization. Collaboration among standards bodies, industry, and academia can yield shared testbeds and evaluation frameworks, helping to translate pilot implementations into scalable, trusted energy-management solutions across manufacturing ecosystems.

Table 2: Key Deployment Challenges and Mitigation Levers for AI-Driven Energy Optimization

Challenge	**Why it limits deployment (as stated)**	**Mitigation levers proposed in the manuscript**
Data quality, availability, interoperability	Heterogeneous IIoT/MES/ERP/EMS data; gaps; legacy integration issues	Data governance; standardization; interoperable data models
High implementation costs & compute needs	Upfront IoT + AI platform costs; ongoing storage/cybersecurity costs	Phased rollouts; shared/managed services; cost-benefit alignment

Resistance to adoption & skills gap	Cultural resistance; limited awareness; shortage of skilled staff	Leadership & change management; upskilling; cross-functional training
Lack of standardized frameworks	Weak comparability/benchmarks; reduced trust/auditability	Reference architectures; benchmarking protocols; certification

Table 2 links deployment barriers, data interoperability, costs, skills gaps, and lack of standards to governance, standardization, phased rollout, and certification strategies, structuring actionable pathways for scalable AI-driven energy optimization implementation.

6. Emerging Trends and Future Directions

6.1 Federated Learning and Edge AI

Decentralized AI approaches such as federated learning (FL) and edge computing allow data processing to occur close to machines, thereby reducing latency and preserving data privacy while enabling real-time energy optimization across distributed manufacturing networks (Fraga-Lamas et al., 2021). By enabling local model updates on resource-constrained devices and minimizing raw data transfers, edge AI supports rapid adaptation to changing shop-floor conditions and energy price signals without centralized data aggregation (Fraga-Lamas et al., 2021), while still benefiting from cross-site learning through FL where permissible data remain on site (Fraga-Lamas et al., 2021). This architecture aligns with Industry 5.0 and Green IoT perspectives that emphasize sustainable digital transitions and human-centric, privacy-preserving analytics in smart manufacturing environments (Fraga-Lamas et al., 2021). The combination of FL and edge inference can be operationalized within digital twins and cyber-physical systems to validate and deploy energy-optimization policies in near-real time across multiple plants (Ono and Okpala, 2025).

However, implementing FL and edge AI at scale presents challenges that must be addressed to unlock their full potential for energy optimization. Technical hurdles include limited edge compute capabilities, the energy cost of running edge inference, data heterogeneity across sites, and the communication overhead inherent to federated learning (Fraga-Lamas et al., 2021). Research into hardware-software co-design for energy-aware edge devices and lightweight FL algorithms is ongoing to mitigate these constraints, while standardized testbeds and interoperable frameworks are needed to enable trustworthy cross-site benchmarking and deployment across manufacturing ecosystems (Fraga-Lamas et al., 2021). As digital twins and cyber-physical systems (CPS) become more tightly integrated with edge-enabled AI, future work should emphasize secure, explainable, and policy-aligned AI workflows that sustain performance gains while safeguarding privacy and compliance across the value chain (Hsu et al., 2023).

6.2 Explainable AI (XAI)

Transparency in AI-driven energy decisions is crucial for trust and regulatory compliance in sustainable manufacturing contexts. Explainable AI (XAI) techniques provide interpretable insights into optimization decisions, enabling human operators and auditors to understand how energy forecasts, load-shifting recommendations, and production schedules are derived (Ezeanyim et al., 2025; Żywiołek, 2024). This interpretability supports governance, risk assessment, and accountability in decision-making processes across industrial energy systems, aligning AI deployments with regulatory expectations and stakeholder confidence (Ezeanyim et al., 2025; Żywiołek, 2024). Moreover, the literature on Industry 5.0 emphasizes human-centric AI design, where explainability and governance are central to the successful adoption and ongoing operation of energy-management solutions (Agostinho et al., 2023; Żywiołek, 2024; Abhilash et al., 2024).

Practical advances in XAI for energy optimization include developing context-aware explanations tailored to different user groups, from plant engineers to executives and auditors, to enhance trust and adoption depth (Emeka et al., 2025; Agostinho et al., 2023). Frameworks that integrate explainability into energy-management dashboards, digital twins, and cyber-physical systems-enabled analytics are increasingly advocated to ensure that each recommended action can be scrutinized and justified in real-time (Emeka et al., 2025; Ezeanyim et al., 2025; Abhilash et al., 2024). The broader discourse also highlights the need for governance structures and standardized explainability protocols to facilitate cross-site benchmarking and regulatory alignment, enabling scalable, auditable AI-powered energy optimization across manufacturing ecosystems (Agostinho et al., 2023; Żywiołek, 2024; Abhilash et al., 2024).

6.3 Integration with Renewable Energy and Smart Grids

AI can balance on-site renewable energy generation with manufacturing demand by forecasting renewable availability and aligning production schedules with grid conditions, enabling tighter coupling between generation, storage, and consumption in smart manufacturing environments (Arévalo et al., 2024; Nwamekwe and Igbokwe, 2024). By integrating AI-driven predictions of solar and wind output with demand signals and energy prices, firms can schedule energy-intensive operations to periods of high renewable availability or favourable grid conditions, thereby reducing reliance on fossil fuel generation and potentially lowering operating costs (Chen et al., 2024). The deployment of microgrids, energy storage, and demand-response strategies, all informed by AI analytics, further enhances the resilience and economic performance of distributed manufacturing networks while promoting higher penetration of renewables (Arévalo et al., 2024). Digital twins and cyber-physical systems (CPS)-enabled optimization provide scenario analysis and real-time coordination across plants and energy networks, supporting multi-site alignment of production with renewable trajectories and grid dynamics (Okezie, 2022; Hsu et al., 2023).

Looking ahead, the integration of AI with renewable energy and smart grids is poised to advance multi-objective optimization that jointly optimizes energy cost, carbon footprint, and production throughput (Nwamekwe and Igbokwe, 2024). As AI-enabled grid analytics mature, manufacturers can participate more actively in energy markets, deploy adaptive demand-side management, and exploit intermittent renewables without compromising reliability (Arévalo et al., 2024). However, realizing these benefits requires robust data ecosystems, interoperable platforms, and governance to ensure transparency and safety in energy decisions, as highlighted by reviews of AI for climate and energy systems (Chen et al., 2024). Collectively, these trends point toward a future where AI-enabled energy optimization acts as a core enabler of sustainable manufacturing, aligning operational flexibility with renewable integration and smarter, cleaner grid operations (Nwamekwe and Igbokwe, 2024; Hsu et al., 2023).

6.4 AI-Driven Circular Economy Approaches

AI supports circular economy strategies by modelling energy use across product life cycles, enabling waste-to-energy recovery, and optimizing material reuse (Lodhi, 2025). By analysing energy and material flows from design through production, use, and end-of-life, AI can reveal opportunities to reduce energy intensity, divert wastes to energy recovery, and maximize the value recovered from materials in remanufacturing and recycling loops (Lodhi, 2025).

These AI-driven circular approaches can also strengthen the integration of energy and materials logistics, supporting design-for-reuse and supply-chain recovery strategies that lower overall energy footprints while maintaining throughput. Through predictive analytics, optimization, and digital-twin-enabled scenario testing, AI helps orchestrate closed-loop systems where energy is recycled or repurposed within the value chain, contributing to superior resource efficiency and sustainability performance across manufacturing ecosystems (Lodhi, 2025).

Conclusion

7.1 Summary of Findings

This study establishes that AI is now a practical, system-wide enabler of energy optimization in manufacturing, not merely a theoretical add-on. The evidence synthesized across the paper shows that AI contributes at three tightly connected decision layers:

1. Energy forecasting and planning (plant/utility interface): AI-driven predictive models support short- and long-horizon demand forecasting, enabling peak-load management, better energy procurement decisions, and preparation for renewable integration. These forecasting capabilities become more reliable when they fuse facility demand signals with production schedules and contextual variables (e.g., environment and operating states). This matters because forecasting is where many energy-saving strategies begin: you cannot optimize what you cannot anticipate.
2. Operational control and scheduling (shop-floor execution): The manuscript shows that AI improves real-time control by shifting operations away from peak demand, dynamically rescheduling energy-intensive tasks, and supporting adaptive control logic (including reinforcement learning). This turns energy management from a static "setpoint rulebook" into a living control strategy that learns from operations and responds to disturbances, pricing changes, and variability in production conditions.
3. Equipment- and system-level efficiency (asset performance + value chain): At the equipment layer, AI-enabled predictive maintenance reduces energy waste linked to degradation, faults, and inefficient operating regimes. At the system layer, AI extends to production planning and supply chain coordination, where optimization can reduce the cumulative energy footprint across interconnected plants, warehouses, and logistics decisions.

The study consolidated position is that AI enables energy optimization from demand prediction through control to cross-network coordination, covering predictive demand forecasting, equipment-level efficiency, and supply chain integration as the core application spectrum.

7.2 Research and Industrial Implications

Implications for research

The study conclusion is positioned that future work should prioritize two research thrusts:

1. Hybrid AI models (accuracy + robustness + deployability): Manufacturing energy problems are multi-source and multi-timescale (equipment signals, facility loads, production logs, and sometimes grid conditions). Pure single-model approaches often fail to generalize when conditions shift. Hybrid modelling, combining forecasting with optimization, and pairing data-driven learning with process constraints offers a path to models that remain stable under real operating variability. In practical terms, this means

designing AI architectures that can ingest heterogeneous data streams and still remain interpretable and governable.

2. Explainability frameworks (trust + compliance + adoption): Energy decisions affect cost, throughput, and emissions. If operators cannot understand why an AI system recommends a load shift, a schedule change, or an equipment intervention, they will resist adoption or override the system. The conclusion therefore emphasizes the need for explainability not as "nice to have," but as a core enabler for industrial use, especially where auditability, safety, and accountability are required.

These directions directly follow the study's argument that scalable deployment depends on both performance and trust: accurate models that cannot be explained rarely survive real production governance.

Implications for industry

For industrial deployment, the conclusion points to three non-negotiable requirements:

1. Investment in digital infrastructure: Scalable AI requires reliable instrumentation and data pipelines (IIoT sensors, smart metering, interoperable MES/ERP/EMS links). Without this, AI becomes a pilot that cannot scale because the underlying data ecosystem cannot sustain continuous learning, monitoring, and updating.
2. Workforce upskilling: AI-enabled energy optimization changes how decisions are made. Engineers, operators, and managers need training not only to "use dashboards," but to interpret model outputs, understand uncertainty and limits, and embed AI recommendations into standard operating routines.
3. Collaborative data ecosystems: Energy optimization often crosses organizational boundaries (grid operators, suppliers, multi-plant networks). The manuscript highlights that collaboration supported by agreed governance rules and shared data standards, is a prerequisite for scaling AI from isolated assets to integrated value-chain energy management.

The core industrial message is that AI benefits are real, but they only materialize when technology deployment is paired with data readiness and human capability building.

7.3 Final Thoughts on the Future of AI in Sustainable Manufacturing

The study closes by framing the next decade as a convergence era: AI + Industry 4.0 infrastructure + renewable energy integration. In this convergence, manufacturing can become a leading sector for decarbonization because it has three advantages:

1. It has high, controllable demand (many loads are schedulable or optimizable).
2. It is increasingly instrumented through Industry 4.0 cyber-physical systems that enable monitoring, simulation (digital twins), and rapid feedback.
3. It can increasingly participate in renewable-aware operations, aligning production schedules with renewable availability, storage dynamics, and grid conditions.

The future-facing claim is that by embedding intelligence into every stage of energy use from forecasting to control to network-wide coordination manufacturing can achieve a dual outcome: competitiveness (cost and productivity) and sustainability (lower emissions and energy intensity), accelerating the transition to a low-carbon industrial economy.

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