AI's Role in Sustainable Manufacturing: Reducing Industrial Waste

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Abstract

As the transition to Industry 5.0 is underway, characterised by the integration of human creativity and collaboration alongside digital transformation, the focal point of various technological interventions is increasingly progressing toward human-centricity and sustainability. Concurrently, the industrial sector faces escalating pressures through global mandates to achieve net zero emissions, where Artificial Intelligence (AI) and Machine Learning (ML) have been proposed to serve as crucial facilitators in advancing sustainable manufacturing. This review critically examines the impact of AI and ML on energy-intensive sectors, with particular focus on the minimisation of industrial waste and carbon emissions, Human-Robot Collaboration (HRC) systems, and smart grid infrastructure. The net environmental impact of AI is also discussed, urging manufacturers to weigh the computational energy required to train these models against the operational savings their implementation generates.

Keywords: Industry 5.0, Artificial Intelligence, Industrial Engineering, Sustainable Manufacturing, Energy Management

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Introduction

The escalating global demand for industrial productivity has concomitantly intensified the imperative for sustainable and energy-efficient manufacturing practices. The integration of artificial intelligence into energy management systems within manufacturing facilities represents a transformative advancement toward optimising energy consumption. With rising concerns about the ethics of AI usage, even within everyday contexts, and as the industrial revolution continues to advance, this paper conducts a comprehensive analysis of existing literature exploring AI's role in sustainable manufacturing, while highlighting the limitations within these studies and the gaps in current research methods for investigating how AI-driven approaches reduce energy costs.

This review examines the application of AI technologies, with particular focus on machine learning algorithms, to enhance energy efficiency in manufacturing environments. It presents a comprehensive analysis of literature addressing how AI-based monitoring tools can minimise industrial waste and emissions, how machine learning models optimise energy usage in factory environments, how smart-grid-enabled manufacturing and Human-Robot Collaboration (HRC) systems are being developed, and how autonomous systems are being implemented for water reuse. Ultimately, the paper discusses how AI-driven approaches can be harnessed to analyse intricate patterns of energy usage and implement strategies that significantly reduce energy costs and mitigate environmental impacts. Nonetheless, within the current research landscape, speculations about ethical, environmental, and social concerns persist, as the literature relies on technocratic and short-term approaches that may overlook these considerations.

Discussion

AI-Based Monitoring Tools to Minimise Industrial Waste and Emissions

As industrial manufacturing is an industry marked by significant global carbon emissions, particularly from energy-intensive sectors including steel, cement, and chemicals, researchers have been adapting to technological changes in the market by implementing novel AI tools to help mitigate industrial waste. Specifically, researchers have employed IoT sensors including gas analysers, energy meters, thermal sensors, and flow meters to collect data on emissions, energy usage, and temperature. A comparative study has demonstrated a notable disparity in the efficacy of AI tools across different industries: while diagnostic accuracy is high, translating detection into tangible production improvements remains complex.

A group of researchers investigating the efficacy of AI tools for air quality and gas monitoring revealed that embedded sensor networks calibrated with machine learning models including KNN, SVM, Random Forest, and Neural Networks were able to achieve high prediction accuracy for particulate matter concentrations (Deters et al., 2017). For detecting hazardous gases in industrial environments, a six-wheeled robot with MQ sensors achieved 98% accuracy in real-time identification of gases including CO_2, LPG, and ethanol (Popescu et al., 2014). These findings suggest that the barrier to identifying pollution has been largely overcome through the application of AI tools.

However, these advances in detection are met with more complex mechanical challenges when it comes to tangible reduction. In the steel manufacturing industry, Gajdzik et al. (2021) uncovered that optimising Electric Arc Furnace systems through Industry 4.0 technologies led to reduced energy consumption, with monitoring through data analysis yielding approximately 3 to 5% energy savings through detecting inefficiencies and identifying abnormal patterns before they become prevalent. In cement production, AI-enabled predictive maintenance tools demonstrated efficiency gains of up to 10% (Feldmann et al., 2019). This discrepancy suggests that the effectiveness of AI interventions may be more pronounced in continuous process industries such as cement production than in variable batch process industries such as steel. While AI can diagnose industrial waste with near-perfect accuracy, the physical constraints of machinery currently make decarbonisation unlikely without a fundamental change in the source of fuel itself.

Machine Learning Models to Optimise Energy Usage in Factory Environments

The integration of machine learning within factory energy systems represents a shift in energy management from a reactive to a proactive approach. There is consensus in the literature that ML approaches can explain significant variability in factory energy systems and thus render energy consumption a variable rather than an inflexible operational cost. Kim et al. (2020) validate this position, utilising a Random Forest algorithm to predict energy consumption in complex facilities and achieving high accuracy with an R2 of approximately 0.88, underscoring the efficacy of these predictive models. This level of explanatory power allows facility managers to isolate variables such as production load or ambient temperature and optimise them dynamically.

A review by Entezari et al. (2023) further demonstrates that AI and ML applications across numerous energy systems, including manufacturing, are increasingly capable of identifying energy-use patterns and strategically enabling reductions. In the broader commercial context, a meta-analysis predicted that the adoption of AI in commercial building systems could reduce energy consumption by 8 to 19% by 2050, with combinations of policy and AI achieving reductions of up to 40% (Ding et al., 2024). These findings collectively suggest that ML models are capable of explaining a large portion of variability in factory energy consumption and can achieve the predictive accuracy required to support meaningful operational optimisation.

Efficacy and Optimisation of Smart Grid-Enabled Manufacturing

Population growth and rising electrical demands have driven the transformation from traditional grids to smart grids, which embody greater innovation and adaptive capacity. The architecture and technologies discussed in the literature, including edge computing, Advanced Metering Infrastructure (AMI), and communication layers, have provided the infrastructure necessary to optimise manufacturing loads, scheduling, demand response, and coordination between the factory and the grid (Goudarzi et al., 2022). IoT-based smart grids have enabled real-time monitoring, two-way communication, and adaptive control that enhance energy management, with research results demonstrating that such systems can reduce transmission losses by 15 to 25% and improve outage detection time by 40 to 60%. The introduction of AMI led to 98% accuracy in real-time energy consumption tracking alongside more optimised results that reflect day-to-day operational changes.

A separate group of researchers assessing the efficiency of smart grid-enabled manufacturing demonstrated that Automated Demand Response (Auto-DR) enhanced energy efficiency, reliability, and flexibility in industrial environments. An aluminium plant was able to provide 70 MW of regulation services to the Midwest ISO as a result of optimising its smart grid-enabled manufacturing tools (Samad, 2012). This finding is particularly significant from a social sustainability perspective, allowing manufacturers to optimise their own costs while supplying energy to the broader grid, successfully linking industrial efficiency with public energy security.

Hybrid Human-Robot Systems for Eco-Efficient Production

The proliferation of automation, artificial intelligence, and big data has characterised Industry 4.0. The next manufacturing paradigm, Industry 5.0, expands on these foundations by reintegrating human factors, reflecting the gradual realisation that human creativity and judgment are indispensable to sustainable and adaptive production systems. In Industry 5.0, robots will be programmed to collaborate safely and effectively alongside human workers. A study implementing AR-enabled HRC for manufacturing tasks demonstrated a 21 to 24% reduction in task completion time and a 57 to 64% reduction in robot idle time compared to a baseline without workspace sharing or an interactive user interface (Hietanen et al., 2019). This efficiency translates into lower energy consumption and reduced material waste through smoother human-robot interactions.

Rahmati et al. (2025) showed that role-adaptive robots in a manufacturing environment achieved a 25% increase in task efficiency and a 20% reduction in energy consumption. In remanufacturing and disassembly contexts, Liu et al. (2019) demonstrated that human-robot collaborative disassembly cells lead to greater resource reuse, increased material recovery, and lower emissions, reinforcing the role of HRC in sustainable production. HRC has also been shown to directly target and eliminate waste types including unnecessary motion, waiting time, and underutilised human skills, key contributors to inefficiency and resource overuse in lean production contexts (Marinelli, 2022). Despite these results, the studies conducted regarding HRC rely on brief data collection windows, raising concerns about the long-term implications for worker wellbeing, psychological health, and cognitive strain that have not yet been fully quantified.

Autonomous Systems for Industrial Water Reuse

The principle that one cannot manage what one does not measure is perhaps most clearly illustrated in industrial water systems. Researchers have developed an intelligent autonomous system capable of disaggregating high-resolution water flow data into distinct end-use events. Known as Autoflow, this automated tool is designed to interpret high-resolution smart meter data to determine where and how water is being consumed (Nguyen et al., 2015). In terms of functionality, the Autoflow system utilises a hybrid analytical approach combining the Hidden Markov Model (HMM) and an Artificial Neural Network (ANN). While the HMM identifies flow patterns associated with distinct water events, the ANN assesses volume, duration, and flow gradients. Dynamic Time Warping (DTW) is additionally employed to detect cyclical signatures from mechanised appliances such as washing machines.

Results from Nguyen et al. (2015) demonstrated exceptional accuracy, with the enhanced hybrid model surpassing the 85% accuracy of the earlier Autoflow prototype. For single events, accuracy rates ranged between 85.9% and 96.1%, while combined events achieved accuracy between 81.8% and 91.5%. These findings suggest that the Autoflow system allows for high-precision water resource management, illustrating the broader versatility of AI strategies for enhanced efficiency across different industrial domains.

Ethics, Discussion, and Limitations

Though AI is taking an increasingly significant role in reducing industrial waste and its technical efficacy is evident, this review identifies several critical gaps that must be addressed before it can be determined whether the operational savings generated by these models outweigh the computational energy required to train them. One primary limitation across the literature is the reliance on controlled-environment simulations rather than empirical, longitudinal data, resulting in limited real-world validation. In Liu et al.'s HRC study, brief data collection windows and short-term observations produced a relatively narrow scope of findings. These limitations fail to account for the long-term psychological and physiological implications of prolonged human-robot collaboration, raising questions about the sustainability of such systems within the social mandate of Industry 5.0.

A further critical limitation lies in the absence of substantive human subjects and socioeconomic consideration. The current literature landscape remains largely technocentric, underscoring the efficacious results of AI and ML usage in sustainable manufacturing while frequently overlooking the ethical and fairness concerns that arise when algorithmic decision-making replaces human judgment. The development of smart grid-enabled manufacturing also raises questions of governance and global equity. As Goudarzi et al. (2022) address infrastructure, the literature largely overlooks the imperative that consistent standards must be applied across all nations, including both high and low-income economies, with the risk that the transition to green manufacturing widens the technological disparity between the global North and South.

Perhaps the most significant limitation lies in the tension surrounding burden shifting in the implementation of these automation tools. While most of the research landscape focuses on deploying AI to reduce operational energy use, it overlooks the importance of conducting lifecycle analyses, a framework imperative for assessing the full environmental impact of robotic edge intelligence system deployments. Factors including the manufacturing of robots and edge devices, the disposal of hardware, and the electronic waste created through deployment must be accounted for (MDPI, 2024). Failure to conduct such analyses risks a scenario in which carbon savings in one area generate a larger environmental footprint elsewhere.

Conclusion

This review has examined the transformative impact of AI automation tools within a sustainable manufacturing context. The technical precision of these tools is evident: near-perfect accuracy has been achieved in monitoring emissions, predicting energy consumption, and optimising water reuse. However, the evidence presented here makes clear that AI and ML, on their own, are not sufficient to meet net-zero goals. Without comprehensive consideration of the environmental impacts of robotic edge intelligence system implementations, manufacturers risk generating even greater industrial waste through the very tools designed to reduce it.

The central argument of this review is that AI and ML tools, though demonstrably generating numerous technical efficiencies, should not be deployed as standalone solutions. Instead, they should function as facilitators, integrated within human-centric approaches that account for worker wellbeing, social equity, and the full lifecycle of the technologies themselves. Future research in this field should emphasise longitudinal studies of worker wellbeing and conduct comprehensive lifecycle assessments of AI and ML tool implementations. Ultimately, for the industrial sector to make meaningful strides in reducing industrial waste and shifting toward meeting global climate mandates in the 21st century, it must ensure that the digital tools of the future are as sustainable in their creation as they are in operation.

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