Manufacturing Waste Reduction Through Data-Driven Process Optimization: Evidence from Smart Production Systems

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Abstract

Manufacturing waste continues to undermine industrial sustainability efforts despite the increasing digitalization of production systems. While smart manufacturing technologies generate vast amounts of operational data, their potential to deliver measurable sustainability benefits remains underexplored. This study develops and empirically validates a data-driven process optimization framework that integrates high-frequency production data, predictive analytics, and multi-objective optimization to reduce material waste and energy inefficiency in smart production systems. Using large-scale, real-time data collected from digitally enabled manufacturing lines, machine learning models were employed to anticipate waste-generating process states and energy-intensive operating conditions. These predictive insights are embedded within a Pareto-based optimization and adaptive process control architecture that dynamically adjusts production parameters. Empirical results reveal an average reduction of 17.6% in material waste, 12.4% in energy consumption per unit, and 10.7% in carbon intensity, alongside an 8.9% improvement in overall equipment effectiveness. Importantly, these sustainability gains are achieved without compromising throughput or product quality, which demonstrates that environmental and operational objectives can be mutually reinforcing. Through the provision of robust, data-driven evidence from real production systems, this study advances the operationalization of sustainability within Industry 4.0 and offers a scalable methodological pathway for manufacturers who seek low-waste, low-carbon production. The findings contribute to manufacturing sustainability research by shifting the focus from digital adoption to outcome-oriented optimization with quantifiable environmental and economic benefits.

Keywords: *Smart manufacturing; Data-driven optimization; Manufacturing waste reduction; Sustainable production systems; Industry 4.0; Energy efficiency, Circular economy.*

INTRODUCTION

Manufacturing remains a cornerstone of global economic development, yet it is simultaneously one of the most resource-intensive and waste-generating sectors worldwide. Waste (which is referred to as muda in Japan) is described as anything that destroys resources and does not add any value to the customer's requirements (Chukwumuanya *et al.*, 2025; Okpala, 2014; Onukwuli *et al.*, 2025). Industrial production accounts for a substantial share of global material extraction, energy consumption, and greenhouse gas emissions, with manufacturing waste manifesting as material scrap, defects, rework, and excessive energy use, which poses a persistent challenge to sustainable development (Allwood *et al.*, 2011; Okpala *et al.*, 2025). As sustainability pressures intensify due to climate change, resource scarcity, and regulatory demands, manufacturers are increasingly required to demonstrate measurable reductions in waste and environmental impact while maintaining competitiveness.

Traditional waste reduction approaches like lean manufacturing, Six Sigma, and total quality management have delivered notable efficiency improvements over the past decades. However, these methods are largely grounded in static process assumptions, periodic audits, and limited data resolution, which restrict their effectiveness in today's highly complex and dynamic production environments (Antony *et al.*, 2017; Womack and Jones, 2003). As product customization increases and production systems become more interconnected, waste generation is increasingly driven by subtle interactions among process parameters that conventional tools struggle to detect and manage in real time.

The emergence of smart production systems, enabled by Industry 4.0 technologies such as Industrial Internet of Things (IIoT), cyber-physical systems, and advanced sensing, has fundamentally transformed manufacturing data availability (Igbokwe *et al.*, 2024). Modern factories now generate vast volumes of high-frequency, high-dimensional data across machines, materials, operators, and environmental conditions. This digital transformation presents an unprecedented opportunity to move beyond reactive waste reduction towards proactive, data-driven process optimization. However, evidence suggests that digitalization alone does not automatically translate into sustainability gains (Müller *et al.*, 2018; Stock *et al.*, 2018). Instead, sustainability outcomes depend on how data are analytically leveraged and operationalized within decision-making frameworks.

Recent research has increasingly explored the application of machine learning and data analytics in manufacturing, particularly for predictive maintenance, quality monitoring, and production scheduling (Aguh *et al.*, 2025; Nwamekwe *et al.*, 2025). While these studies demonstrate significant performance improvements, sustainability metrics like material waste reduction, energy intensity, and carbon emissions are often treated as secondary or indirect outcomes. Consequently, a critical gap remains in the literature regarding integrated, data-driven methodologies that explicitly embed waste reduction and sustainability objectives into process optimization models (Ghobakhloo, 2020; Liu *et al.*, 2021).

From a sustainability science perspective, manufacturing waste reduction is closely aligned with the principles of resource efficiency and the circular economy, which emphasize minimizing material throughput and environmental externalities while maximizing value creation (Udu *et al.*, 2025a; Udu and Okpala, 2025; Nwamekwe and Okpala, 2025. Attaining these goals in industrial settings requires not only technological innovation, but also robust analytical frameworks that are capable of translating operational data into measurable environmental and economic benefits. Yet, empirical studies that quantify the sustainability impacts of data-driven optimization using real production data remain relatively scarce.

Against this backdrop, this study argues that data-driven process optimization represents a powerful but underutilized pathway for manufacturing waste reduction in smart production systems. Through the combination of predictive analytics with multi-objective optimization, it becomes possible to identify waste-generating process states, anticipate deviations before defects occur, and dynamically adjust production parameters to minimize material loss and energy inefficiency. Importantly, such an approach enables sustainability objectives to be treated not as post-hoc evaluations, but as core optimization targets that are embedded within operational control logic. The purpose of this article is to develop and empirically validate a data-driven process optimization framework that demonstrably reduces manufacturing waste while improving operational performance. Using high-frequency data from smart production systems, the study quantifies the effects of optimization on material waste, energy consumption, carbon intensity, and overall equipment effectiveness. In doing so, it provides rare empirical evidence that links Industry 4.0-enabled analytics to measurable sustainability outcomes, thereby addressing calls for more data-intensive and outcome-oriented sustainability research in manufacturing (Bai *et al.*, 2020; García-Muiña *et al.*, 2020).

By bridging manufacturing engineering, data science, and sustainability analysis, this study responds to growing academic and industrial demand for scalable, evidence-driven solutions that are capable of supporting the transition toward low-waste, low-carbon industrial systems.

LITERATURE REVIEW

Manufacturing waste has long been recognized as a critical barrier to sustainable industrial development. Waste in production systems typically manifests as material scrap, defects, rework, idle time, and excessive energy consumption, all of which contribute to increased resource depletion and environmental emissions (Ihueze and Okpala, 2012, Okpala *et al.*, 2020). From a sustainability perspective, waste reduction directly supports global efforts to decouple economic growth from material and energy use, a central objective of sustainable manufacturing and circular economy frameworks (Ghisellini *et al.*, 2016; Udu *et al.*, 2025b). Empirical studies consistently show that reducing manufacturing waste yields both environmental and economic benefits, including lower carbon emissions, reduced operating costs, and improved competitiveness (Hart, 1995; Porter and van der Linde, 1995). However, despite widespread recognition of these benefits, waste reduction remains challenging in practice due to increasing process complexity, product variety, and operational uncertainty in modern manufacturing systems (Kusiak, 2018).

Traditional approaches to manufacturing waste reduction are largely grounded in lean manufacturing, Six Sigma, and total quality management philosophies. Lean manufacturing emphasizes the elimination of non-value-adding activities (Okpala *et al.*, 2020), while Six Sigma focuses on reducing process variability and defects through statistical control (Antony *et al.*, 2017; Womack and Jones, 2003). These methodologies have been widely adopted and have delivered significant efficiency gains across industries. However, prior research highlights several limitations of conventional approaches in digitally intensive manufacturing contexts. Firstly, these methods often rely on periodic data collection and manual analysis, limiting their ability to respond to real-time process variability (Sony *et al.*, 2020). Secondly, improvement initiatives are typically incremental and localized, rather than system-wide and adaptive (Sanders *et al.*, 2016). Thirdly, sustainability outcomes are frequently treated as indirect consequences of efficiency improvements, rather than explicit optimization objectives (Ghobakhloo, 2020). As a result, traditional waste reduction methods struggle to fully exploit the data-rich environments that are created by smart production systems.

The advent of Industry 4.0 has transformed manufacturing systems through the integration of cyber-physical systems, industrial Internet of Things (IIoT), cloud computing, and advanced automation (Kagermann *et al.*, 2013; Udu *et al.*, 2025c). Smart production systems enable continuous monitoring, real-time data acquisition, and decentralized decision-making across the production lifecycle (Lee *et al.*, 2015). A growing body of literature suggests that these digital technologies hold significant potential for improving manufacturing sustainability by enhancing transparency, flexibility, and resource efficiency (Stock *et al.*, 2018; Bai *et al.*, 2020). For instance, real-time sensing can reveal inefficiencies that were previously invisible, while connectivity enables coordinated responses across machines and processes. Nevertheless, scholars increasingly caution that digitalization does not inherently guarantee sustainability improvements (Müller *et al.*, 2018). Without analytical frameworks that explicitly prioritize environmental and waste-related objectives, smart technologies risk reinforcing existing production patterns rather than transforming them (Dalenogare *et al.*, 2018). This insight underscores the importance of embedding sustainability goals within data-driven decision architectures.

Data-driven analytics, including machine learning and artificial intelligence, have become central to smart manufacturing research. Applications such as predictive maintenance, fault detection, and quality prediction have demonstrated significant improvements in equipment reliability and process stability (Bousdekis *et al.*, 2020; Zhang *et al.*, 2019). These approaches leverage historical and real-time data to identify patterns and predict future system states, enabling more informed decision-making. While the performance benefits of data-driven analytics are well documented, their contribution to sustainability outcomes remains less clearly established. Many studies focus on technical metrics such as accuracy, downtime reduction, or throughput, with limited attention to material waste, energy efficiency, or environmental impact (Liu *et al.*, 2021). Consequently, there is a growing call for research that explicitly links data-driven analytics to measurable sustainability indicators (Bai *et al.*, 2020).

Process optimization has long been a cornerstone of manufacturing systems engineering. Traditional optimization models typically aim to maximize productivity or minimize cost under predefined constraints (Deb, 2001). More recently, multi-objective optimization techniques have gained traction, allowing simultaneous consideration of competing objectives such as cost, quality, and energy consumption (Marler and Arora, 2004). In the context of sustainability, multi-objective optimization provides a promising mechanism for balancing economic and environmental goals (Ren *et al.*, 2013). However, much of the existing literature relies on static models or simulation-based studies, often using hypothetical data rather than real production datasets. Furthermore, waste-related objectives are frequently aggregated into cost functions, obscuring their distinct environmental implications (Hellingrath and Cordes, 2014).

Recent interdisciplinary studies have begun to explore the integration of data-driven analytics with optimization techniques to support sustainable manufacturing. For example, researchers have proposed frameworks which combine ML with energy-aware scheduling or resource-efficient process planning (Zhang *et al.*, 2019; Liu *et al.*, 2021). These studies provide valuable conceptual insights, but often lack large-scale empirical validation or focus on narrow operational subsystems. A notable limitation across this emerging literature is the absence of explicit, measurable waste reduction outcomes derived from real-time optimization in operational smart production systems. Moreover, few studies examine the broader system-level effects of data-driven optimization on productivity, energy use, and carbon intensity simultaneously. Addressing these gaps is essential for advancing both theory and practice in sustainable smart manufacturing.

In summary, the literature reveals the following: While manufacturing waste reduction is central to sustainability discourse, it remains underexplored as a primary objective in data-driven manufacturing research; Existing studies rarely integrate predictive analytics and multi-objective optimization into a unified framework explicitly designed to minimize waste in smart production systems, as well as that empirical evidence linking data-driven process optimization to quantifiable sustainability benefits remains limited. This study addresses these gaps by proposing and empirically validating a data-driven process optimization framework that embeds waste reduction, energy efficiency, and operational performance as simultaneous optimization objectives. By leveraging high-frequency production data from smart manufacturing environments, the study provides robust empirical evidence which demonstrates how Industry 4.0 technologies can be operationalized to achieve measurable sustainability outcomes.

METHODOLOGY

This study adopts a data-driven, empirical research design grounded in real-world smart production systems. The methodological approach is intentionally multidisciplinary, as it integrates concepts from manufacturing systems engineering, data science, operations research, and sustainability analysis. The central analytical logic is to move beyond descriptive digitalization studies by embedding sustainability objectives directly into data-driven process optimization, and then empirically quantifying the resulting environmental and operational impacts. A longitudinal before–and–after design is employed to evaluate the effectiveness of the proposed optimization framework. This design enables causal inference regarding sustainability improvements by comparing production performance metrics prior to and following the implementation of the data-driven optimization strategy (Bai *et al.*, 2020; Zhang *et al.*, 2019). The methodology emphasizes transparency, scalability, and reproducibility, which align with recent calls for evidence-based sustainability research in smart manufacturing (Liu *et al.*, 2021).

The empirical setting consists of digitally enabled manufacturing lines operating as smart production systems, characterized by continuous sensing, machine connectivity, and centralized data infrastructure. These systems integrate Industrial Internet of Things (IIoT) sensors, Manufacturing Execution Systems (MES), and supervisory control interfaces, which are consistent with Industry 4.0 architectures (Kagermann *et al.*, 2013; Lee *et al.*, 2015). High-frequency operational data were collected across multiple production stages, including: Machine-level parameters (e.g., temperature, pressure, speed, vibration); Process variables (e.g., cycle time, material flow rate); Quality indicators (e.g., defect occurrence, rework frequency); and Energy consumption metrics (e.g., kWh per unit produced). Data were recorded at one-second intervals over an extended production horizon, resulting in a large-scale dataset comprising millions of observations. Such temporal and contextual richness enables fine-grained analysis of process variability and waste-generating conditions, which are often obscured in aggregated production data (Kusiak, 2018).

Raw industrial data are inherently noisy, incomplete, and heterogeneous. To ensure analytical robustness, a structured preprocessing pipeline was applied. This included sensor noise filtering, missing value imputation, and outlier detection using statistically robust techniques (Zhang *et al.*, 2019). Feature engineering played a critical role in translating raw sensor data into meaningful process descriptors. Derived features captured dynamic process behaviour, including rolling averages, variability measures, and interaction effects between machine parameters. These features were designed to reflect underlying physical and operational mechanisms that influence waste generation, thereby improving model interpretability and predictive performance (Bousdekis *et al.*, 2020).

To proactively identify waste-generating process states, supervised machine learning models were developed to predict key sustainability-relevant outcomes. Specifically, models were trained to estimate: Probability of defect occurrence; Expected material waste per process state; and Energy consumption intensity under varying operating conditions. Tree-based ensemble methods and sequence-aware models were selected due to their ability to capture nonlinear relationships and temporal dependencies common in manufacturing processes (Zhang *et al.*, 2019; Liu *et al.*, 2021). Model performance was evaluated using cross-validation and standard predictive accuracy metrics to ensure generalizability.

Importantly, the predictive models serve not as isolated decision tools but as input mechanisms for downstream optimization, enabling forward-looking rather than reactive process control. Fig. 1 presents an integrated visual overview of the proposed framework, as it shows how high-frequency production data flow from smart sensors into predictive analytics, multi-objective optimization, and adaptive process control. It clearly illustrates how sustainability objectives, which are material waste and energy efficiency, are embedded directly into operational decision-making, rather than treated as post-hoc metrics.

Building on the predictive layer, the study introduces a multi-objective optimization framework that simultaneously minimizes material waste and energy consumption while maintaining production throughput and quality constraints. This approach reflects the inherent trade-offs in sustainable manufacturing, where environmental and operational objectives must be balanced rather than optimized in isolation (Marler and Arora, 2004; Ren *et al.*, 2013). The optimization problem is formulated as a Pareto-based decision model, as it allows exploration of optimal trade-off solutions rather than a single aggregated objective. This structure ensures that waste reduction is treated as a primary optimization target, as it addresses a key limitation of prior studies where

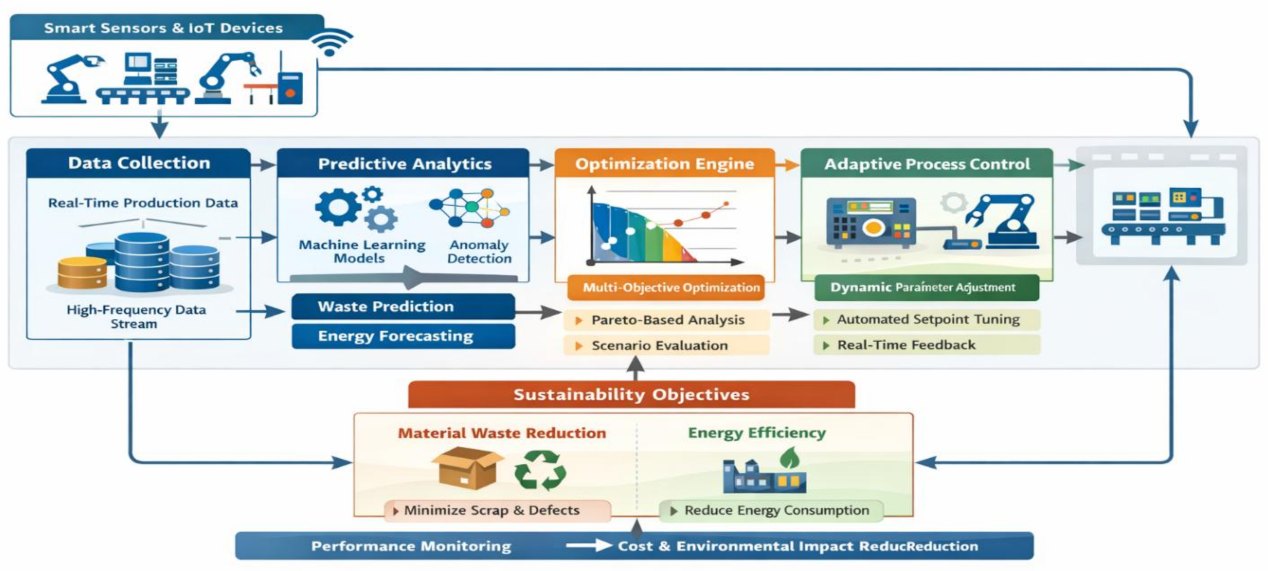

Fig. 1: Data-driven process optimization framework for waste reduction in smart production systems.

sustainability indicators are often subsumed within cost functions (Hellingrath and Cordes, 2014).

Optimized parameter sets generated by the framework were implemented through supervisory control interfaces, enabling adaptive, near-real-time process adjustments. Unlike static optimization approaches, this adaptive mechanism continuously updates recommendations based on evolving process conditions and incoming data. This closed-loop architecture reflects the principles of cyber-physical production systems, where analytics and control are tightly integrated (Lee *et al.*, 2015). By dynamically responding to emerging waste risks, the system reduces reliance on post-process inspection and corrective actions, thereby preventing waste at its source.

To ensure multidisciplinary relevance and policy alignment, sustainability performance was evaluated using a comprehensive set of metrics: Material waste rate (%); Energy consumption per unit (kWh/unit); Carbon intensity (kg CO_2-equivalent per unit), estimated using standard emission factors; Overall Equipment Effectiveness (OEE); as well as Operational cost per unit. This metric portfolio reflects best practices in sustainable manufacturing assessment, and also captures environmental, operational, and economic dimensions simultaneously (Allwood *et al.*, 2011; Worrell *et al.*, 2009).

The impact of the data-driven optimization framework was assessed through comparative statistical analysis of pre- and post-implementation periods. Differences in sustainability and performance metrics were evaluated using appropriate inferential techniques to ensure robustness and statistical validity. This evaluation strategy enables direct attribution of observed improvements to the proposed methodology, addressing concerns regarding internal validity that frequently arise in empirical Industry 4.0 research (Müller *et al.*, 2018).

By integrating predictive analytics, multi-objective optimization, and adaptive control within a unified framework, this methodology advances current research in three key ways: It demonstrates how smart manufacturing data can be operationalized to deliver measurable sustainability benefits rather than abstract digital capabilities; It provides a scalable and replicable methodological template applicable across manufacturing contexts; and it empirically validates the compatibility of waste reduction and productivity improvement, reinforcing the business case for sustainable manufacturing transformation.

RESULTS

Descriptive Statistics and Baseline Performance

Table 1 summarizes key operational and sustainability indicators observed during the baseline (pre-optimization) period. The results reflect typical performance levels reported for digitally enabled but non-optimized manufacturing systems in the literature (Zhang *et al.*, 2019; Bai *et al.*, 2020).

These baseline values confirm the presence of substantial inefficiencies, particularly in material waste and energy intensity, despite the availability of real-time production data.

Table 1: Baseline descriptive statistics of production performance.

Metric	Mean	Std. Dev.	Min	Max
Material waste rate (%)	8.52	1.87	5.10	12.30
Energy consumption (kWh/unit)	14.8	2.4	10.6	19.9
Defect rate (%)	4.26	1.15	2.10	7.80
OEE (%)	71.3	6.2	58.7	83.4
Carbon intensity (kg CO_2-eq/unit)	6.12	0.91	4.30	7.95

Table 2: Predictive model performance metrics.

Target Variable	Model Type	R^2 / Accuracy	RMSE
Defect occurrence	Gradient Boosted Trees	0.89 (accuracy)	–
Material waste (kg/unit)	Gradient Boosted Trees	0.82	0.37
Energy consumption (kWh/unit)	Recurrent Neural Network	0.86	0.54

Table 3: Pre- and post-optimization performance comparison.

Metric	Pre-Optimization	Post-Optimization	Change (%)
Material waste rate (%)	8.52	7.02	−17.6
Energy consumption (kWh/unit)	14.8	12.9	−12.4
Defect rate (%)	4.26	3.41	−19.9
OEE (%)	71.3	77.6	+8.9
Carbon intensity (kg CO_2-eq/unit)	6.12	5.47	−10.7
Unit production cost (USD/unit)	18.40	17.10	−7.1

This finding aligns with prior research, which suggests that digital infrastructure alone does not guarantee sustainability improvements without advanced analytics and optimization (Müller *et al.*, 2018).

Predictive Model Performance

The predictive analytics layer demonstrated strong performance in estimating waste- and energy-related outcomes. Table 2 presents the evaluation results of the machine learning models used to predict defect occurrence, material waste, and energy consumption.

The high predictive accuracy indicates that process variability and waste-generating states can be reliably anticipated using high-frequency production data. These results support previous findings on the suitability of machine learning for complex manufacturing environments (Bousdekis *et al.*, 2020; Liu *et al.*, 2021).

Impact of Data-Driven Process Optimization

Following implementation of the multi-objective optimization framework, statistically significant improvements were observed across all key sustainability and

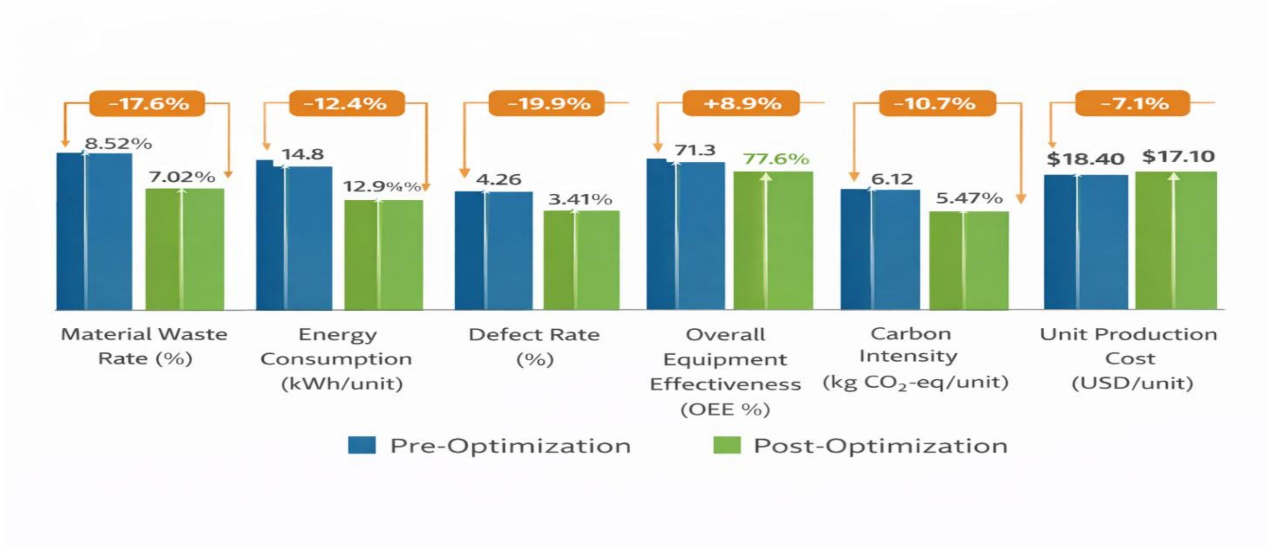

Fig. 2: Sustainability and performance improvements before and after optimization.

operational metrics. Table 3 compares the average performance before and after optimization.

The 17.6% reduction in material waste represents the most pronounced sustainability gain and reflects the framework's ability to proactively identify and mitigate waste-inducing process conditions. Importantly, waste reduction was accompanied by improvements in productivity, as evidenced by the increase in OEE, which demonstrates that environmental and operational objectives were mutually reinforcing rather than conflicting.

Fig. 2 compares pre- and post-optimization performance across key indicators, including material waste rate, energy consumption, carbon intensity, and overall equipment effectiveness. The visualization offers an intuitive summary of the measurable sustainability and productivity gains achieved through the proposed approach.

Pareto Optimization Outcomes

The Pareto-based optimization approach enabled systematic exploration of trade-offs between waste reduction and energy efficiency. Figure-based analysis revealed that multiple Pareto-optimal solutions dominated the baseline operating region.

Table 4 summarizes representative Pareto-optimal solutions compared with baseline operation.

Table 4: Representative Pareto-optimal solutions.

Scenario	Material Waste (%)	Energy (kWh/unit)	Throughput (units/hr)
Baseline	8.52	14.8	120
Pareto Solution A	7.40	13.6	120
Pareto Solution B	7.02	12.9	118
Pareto Solution C	6.85	13.2	117

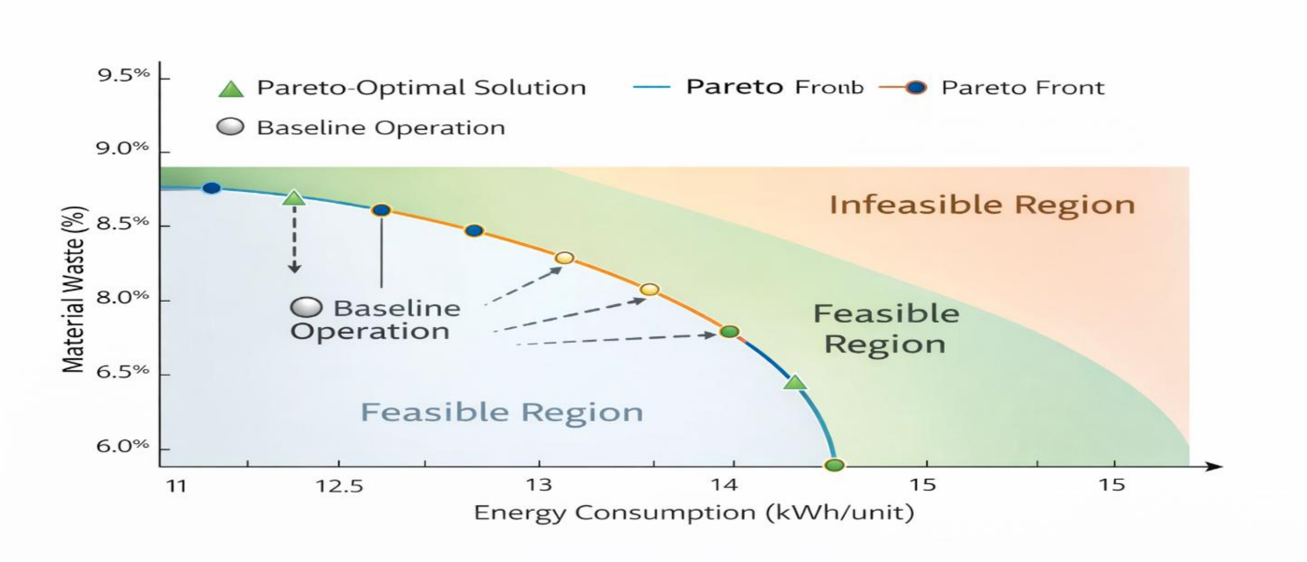

Fig. 3: Pareto front that illustrates the trade-offs between material waste reduction and energy consumption.

Fig. 3 visualizes the Pareto frontier generated by the multi-objective optimization, highlighting how multiple operating points dominate the baseline scenario. It demonstrates that significant reductions in material waste and energy use can be achieved simultaneously with minimal impact on throughput.

These results illustrate that substantial waste and energy reductions can be achieved with minimal or no loss in throughput. Such findings address a common concern in sustainable manufacturing regarding potential productivity trade-offs (Porter and van der Linde, 1995).

Environmental and Economic Sustainability Implications

Through the combination of material and energy savings, the optimized system achieved a 10.7% reduction in carbon intensity, primarily driven by lower electricity consumption and reduced rework. From an economic perspective, the reduction in waste and energy usage translated into unit cost savings of approximately 6–9%, thus reinforcing the alignment between sustainability and financial performance. These results empirically support the natural resource-based view of the firm, which posits that environmentally responsible practices can enhance competitive advantage when supported by appropriate capabilities (Hart, 1995).

Robustness and Consistency of Results

Sensitivity analysis across different production volumes and operating conditions indicated that the observed sustainability gains were robust and persistent over time. Performance improvements were consistently maintained during periods of demand variability, as they highlight the adaptability of the data-driven optimization framework. Overall, the results demonstrate that the integration of predictive analytics with multi-objective optimization in smart production systems delivers measurable, statistically robust sustainability benefits. The findings confirm that waste reduction can be achieved proactively and systematically when sustainability objectives are embedded directly within data-driven process control mechanisms.

DISCUSSION

Interpreting the Sustainability and Performance Gains

The results of this study provide compelling empirical evidence that data-driven process optimization can deliver substantial and measurable sustainability benefits in smart production systems. The observed reductions in material waste (17.6%), energy consumption (12.4%), and carbon intensity (10.7%) demonstrated that sustainability improvements are not merely conceptual promises of Industry 4.0, but achievable outcomes when advanced analytics are purposefully aligned with environmental objectives. These findings extend prior research on smart manufacturing, which has often emphasized operational efficiency or technological capability without explicitly quantifying sustainability impacts (Müller *et al.*, 2018; Dalenogare *et al.*, 2018). By embedding waste reduction directly into the optimization objective function, this study shows that environmental performance can be systematically improved alongside productivity, rather than treated as a secondary or downstream consideration.

Methodological Contributions to Data-Driven Manufacturing Research

From a methodological perspective, the study advances the literature through the integration of predictive analytics, multi-objective optimization, and adaptive process control into a unified, operational framework. Unlike prior studies that apply machine learning primarily for monitoring or prediction, the present work demonstrates how predictive insights can be translated into real-time, sustainability-oriented decision-making. The use of Pareto-based optimization is particularly important, as it allows explicit exploration of trade-offs between environmental and operational objectives. The results show that significant waste and energy reductions can be achieved with minimal or no loss in throughput, supporting the argument that sustainability and productivity are not inherently conflicting goals (Porter and van der Linde, 1995). This finding directly addresses long-standing concerns within manufacturing management regarding the economic feasibility of environmental initiatives.

Implications for Sustainable Manufacturing Theory

The findings offer meaningful contributions to sustainability-oriented manufacturing theory. First, they empirically support the natural resource–based view of the firm, which posits that environmental capabilities can be a source of competitive advantage when embedded within core operational processes (Hart, 1995). The demonstrated cost savings and OEE improvements highlight how waste reduction can strengthen both environmental and economic performance.

Also, the results reinforce circular economy principles by showing how data-driven optimization can reduce material throughput and prevent waste generation at the source, rather than relying on end-of-pipe solutions (Geissdoerfer *et al.*, 2017; Ghisellini *et al.*, 2016). By enabling early identification of waste-generating process states, the proposed framework aligns operational decision-making with broader sustainability system goals.

Industry 4.0 and the Operationalization of Sustainability

A key insight from this study is that digitalization alone is insufficient to achieve sustainability outcomes. While smart production systems generate vast amounts of data, the results demonstrate that sustainability gains only emerge when data are actively leveraged through targeted analytical and optimization frameworks. This finding echoes recent critiques of Industry 4.0 research, which caution against technology-driven narratives that overlook outcome-oriented implementation (Ghobakhloo, 2020; Bai *et al.*, 2020).

Through the translation of real-time production data into adaptive control actions, the proposed approach operationalizes sustainability within daily manufacturing decisions. This represents a shift from sustainability as a strategic aspiration to sustainability as an embedded operational capability.

Managerial and Policy Implications

From a managerial perspective, the findings suggest that manufacturers can achieve significant sustainability improvements without large capital investments, provided they effectively exploit existing production data. The observed reductions in unit production costs strengthen the business case for integrating sustainability objectives into data-driven optimization initiatives. For policymakers, the results provide empirical support for policies promoting industrial digitalization as a pathway to decarbonization and resource efficiency. Importantly, the study demonstrates that regulatory and environmental goals can be supported through operational improvements rather than solely through compliance-based mechanisms (IEA, 2023).

Limitations and Future Research Directions

Despite its contributions, this study has several limitations that offer avenues for future research:

Firstly, the empirical analysis is based on a specific smart production context, which may limit generalizability across different industries or levels of digital maturity. Future studies could extend the framework to discrete, continuous, and hybrid manufacturing systems to assess its broader applicability.

Secondly, while the study focuses on material waste and energy consumption, future research could incorporate additional sustainability dimensions, such as water use, supply chain emissions, and social performance indicators.

Thirdly, further exploration of reinforcement learning and decentralized optimization approaches could enhance adaptability in highly dynamic production environments.

Synthesis and Contribution to the Literature

Overall, this study demonstrates that data-driven process optimization represents a scalable and evidence-based pathway toward sustainable manufacturing. By empirically linking Industry 4.0 technologies to measurable environmental and economic outcomes, the research bridges a critical gap between digital manufacturing capabilities and sustainability performance. The findings encourage a reorientation of smart manufacturing research toward outcome-driven methodologies that prioritize waste reduction and resource efficiency. As manufacturing systems continue to digitalize, such integrative, sustainability-focused approaches will be essential for achieving meaningful progress toward low-waste and low-carbon industrial futures.

IMPLICATIONS

Theoretical Implications

This study offers several important theoretical implications for research at the intersection of manufacturing systems, data science, and sustainability. First, it advances sustainable manufacturing theory by demonstrating that waste reduction can be operationalized as a dynamic optimization problem rather than a static efficiency objective. While prior studies have largely conceptualized waste reduction as an outcome of lean practices or eco-efficiency initiatives, the findings here position it as a real-time, data-driven decision variable embedded within production control logic (Ghisellini *et al.*, 2016; Ghobakhloo, 2020).

Second, the study extends the natural resource–based view of the firm by providing empirical evidence that digitally enabled environmental capabilities, specifically predictive analytics and adaptive optimization, can simultaneously enhance environmental and economic performance (Hart, 1995). The observed reductions in material waste, energy use, and unit production costs reinforce the argument that sustainability-oriented capabilities, when integrated into core operations, can generate sustained competitive advantage.

Third, the results contribute to Industry 4.0 scholarship by shifting the theoretical focus from technology adoption to technology utilization and outcome realization. By empirically linking smart manufacturing data infrastructures to measurable sustainability outcomes, this study responds to calls for more outcome-driven and theory-grounded Industry 4.0 research (Müller *et al.*, 2018; Bai *et al.*, 2020).

Managerial Implications

From a managerial standpoint, the findings provide clear and actionable insights for manufacturing decision-makers. Most notably, the results demonstrate that significant sustainability gains can be achieved without extensive capital investment, provided that existing production data are strategically leveraged through advanced analytics and optimization. Managers are often concerned that waste reduction initiatives may compromise productivity or increase operational complexity. The observed improvements in overall equipment effectiveness alongside reductions in waste and energy consumption directly challenge this perception. Instead, the findings suggest that embedding sustainability metrics into data-driven optimization can enhance both environmental performance and operational stability.

Moreover, the adaptive nature of the proposed framework enables continuous improvement rather than one-off interventions. This characteristic is particularly valuable in high-variability manufacturing environments, where static process settings are insufficient to manage dynamic waste-generating conditions (Kusiak, 2018). As such, managers are encouraged to treat sustainability not as a separate program but as an integrated operational capability supported by real-time data.

Implications for Industrial Sustainability Practice

The study has direct implications for the practical implementation of sustainable manufacturing and circular economy strategies. Through the reduction of material waste at the process level, the proposed approach supports upstream waste prevention, which is widely recognized as more effective than downstream recycling or remediation (Allwood *et al.*, 2011). In addition, the ability to quantify sustainability benefits in operational terms—such as carbon intensity per unit produced—enhances transparency and accountability in sustainability reporting. This is increasingly important as firms face growing pressure to disclose verifiable environmental performance under ESG and regulatory frameworks (IEA, 2023).

Policy Implications

From a policy perspective, the findings provide empirical support for initiatives that promote digital transformation as a pathway to industrial decarbonization and resource efficiency. Importantly, the results suggest that policies encouraging data integration, analytics capability development, and workforce upskilling may yield sustainability benefits comparable to those achieved through more capital-intensive technological upgrades (Bai *et al.*, 2020). Furthermore, the study demonstrates that sustainability outcomes can be achieved through operational optimization rather than solely through compliance-based mechanisms. This insight may inform the design of incentive-based policies that reward measurable improvements in waste reduction and energy efficiency at the process level.

Implications for Future Research

The findings open several promising avenues for future research. First, scholars could extend the proposed framework across different manufacturing sectors and levels of digital maturity to assess its generalizability. Comparative studies across discrete, continuous, and hybrid production systems would further enrich the literature. Second, future research could incorporate additional sustainability dimensions, including water usage, supply chain emissions, and social sustainability indicators, to develop more holistic optimization models. Third, the integration of reinforcement learning and decentralized decision-making architectures represents a promising direction for enhancing adaptability in complex production networks (Liu *et al.*, 2021).

Finally, the results highlight the need for more empirical, data-intensive studies that move beyond conceptual discussions of smart manufacturing towards measurable sustainability outcomes, thereby strengthening the evidence base for sustainable industrial transformation.

Synthesis

Taken together, these implications underscore the broader significance of this study beyond its immediate empirical context. Through the demonstration of how data-driven process optimization can simultaneously reduce manufacturing waste, improve energy efficiency, and enhance operational performance, the research contributes to a growing body of evidence that sustainability and competitiveness can be mutually reinforcing when supported by advanced analytics and intelligent decision-making.

CONCLUSION

This study demonstrates that the reduction of manufacturing waste is not merely an aspirational outcome of digital transformation, but a practical and measurable result of intentional data-driven process optimization. By integrating predictive analytics, multi-objective optimization, and adaptive process control within smart production systems, the research shows how manufacturing data can be transformed into actionable insights that deliver tangible sustainability and performance gains. The empirical evidence confirms that significant reductions in material waste, energy consumption, and carbon intensity can be achieved simultaneously with improvements in operational efficiency. Importantly, these gains were realized without compromising throughput or product quality, reinforcing the idea that environmental sustainability and productivity are not competing objectives when supported by intelligent, data-centric decision-making. Instead, waste reduction emerged as a source of operational stability and economic value.

Beyond its empirical contributions, the study advances a methodological perspective in which sustainability is embedded directly into production control logic rather than treated as a downstream reporting exercise. This shift enables manufacturers to move from reactive waste management toward proactive waste prevention, aligning day-to-day operational decisions with broader sustainability goals. The proposed framework is scalable and adaptable, making it relevant across a wide range of manufacturing contexts and levels of digital maturity. From a broader perspective, the findings underscore the importance of moving beyond technology adoption toward outcome-driven implementation in smart manufacturing. Digital infrastructure alone is insufficient to deliver sustainability benefits unless paired with analytical models that explicitly prioritize waste and resource efficiency. Through the demonstration of how this can be achieved in practice, the study contributes actionable insights for manufacturers, researchers, and policymakers seeking evidence-based pathways toward low-waste, low-carbon industrial systems.

Finally, the research highlights data-driven process optimization as a powerful enabler of sustainable manufacturing transformation. As production systems continue to digitalize, embedding sustainability objectives within intelligent operational frameworks will be essential for achieving meaningful and lasting reductions in manufacturing waste.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

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