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Optimization of Smart Manufacturing Systems through Renewable Energy Integration and Sustainable Material Utilization

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Abstract
The transition towards sustainable and intelligent manufacturing requires holistic frameworks that integrate renewable energy, sustainable materials, and advanced digital technologies. This study develops a data-driven, multi-objective optimization framework for smart manufacturing systems that simultaneously enhances productivity and reduces environmental impact. A digital twin–enabled hybrid AI–NSGA-II model was designed to optimize production cost, carbon emissions, energy efficiency, and material circularity. The model was implemented in a precision machining facility that operates under a hybrid solar–grid energy configuration using real-time data across energy, production, and material dimensions. Results revealed significant sustainability gains over the baseline operation: 12.8% reduction in production cost, 24.5% reduction in carbon emissions, 32.7% improvement in energy efficiency, and 26-point increase in the Material Circularity Index (MCI), accompanied by a 17.6% increase in productivity. Renewable energy contribution rose from 21% to 58% of total electricity demand, and recycled or bio-based material utilization increased from 18% to 46%. Comparative evaluation against benchmark models confirmed superior performance across all sustainability metrics. The proposed framework demonstrates that the integration of renewable energy utilization, circular material strategies, and digital twin–driven optimization can achieve measurable environmental and economic benefits without compromising operational efficiency. The findings offer a scalable pathway for industries that are transitioning towards carbon-neutral and circular manufacturing under the emerging Industry 5.0 paradigm.
Keywords: *smart manufacturing, renewable energy integration, sustainable materials, digital twin, multi-objective optimization, circular economy, energy efficiency, Industry 5.0*

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I. Introduction

Global manufacturing industries are at a critical juncture as they strive to reconcile the twin imperatives of technological advancement and environmental sustainability. The rapid evolution of Industry 4.0 which is driven by digital technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Cyber-Physical Systems (CPS), has led to the emergence of Smart Manufacturing Systems (SMS) which are capable of real-time monitoring, data-driven decision-making, and autonomous optimization (Tao et al., 2019; Ghobakhloo, 2020). While these systems have significantly improved productivity and operational flexibility, the environmental footprint of manufacturing remains substantial. The industrial sector accounts for nearly 30% of global final energy use and contributes approximately 20% of direct CO_2 emissions (International Energy Agency [IEA], 2023). To align manufacturing with global climate goals, the integration of renewable energy sources and sustainable materials within smart, data-driven manufacturing frameworks is imperative (Li et al., 2021; Kamble et al., 2020).

1.1 Smart Manufacturing as a Driver of Sustainable Production

Smart manufacturing leverages digital technologies to enhance operational efficiency and responsiveness through advanced sensing, connectivity, and analytics (Tao et al., 2019). IoT devices play a pivotal role in these smart manufacturing supply chains by collecting and exchanging data across various stages of the manufacturing process, from raw material sourcing to final product delivery (Nwankwo et al., 2024; Okpala et al., 2025a).

However, the majority of optimization research in smart manufacturing has historically prioritized cost minimization and productivity enhancement, often at the expense of energy and material sustainability (Zhang and Jia, 2023). Recent studies have called for the next phase of Industry 4.0 - Sustainable Industry 5.0, which integrates human-centric design and environmental intelligence into digital manufacturing ecosystems

(Nahavandi, 2019; Okpala and Nwankwo, 2025a). This transition requires methodological frameworks that couple operational efficiency with sustainability performance metrics such as carbon intensity, resource circularity, and renewable energy utilization (Yadav et al., 2020).

1.2 Renewable Energy Integration in Manufacturing Systems

The integration of Renewable Energy Sources (RES) into industrial systems has emerged as a key pathway to decarbonization. Hybrid renewable–grid energy models that utilizes solar photovoltaics, wind power, and bioenergy have demonstrated energy cost reductions of up to 25% and emission reductions exceeding 40% in selected manufacturing settings (Hossain et al., 2022; Li et al., 2021). However, challenges such as intermittency, variability, and synchronization between production cycles and renewable supply profiles hinder large-scale implementation (Shahriar et al., 2022).

Advanced energy management frameworks which employ Machine Learning (ML), Digital Twins (DTs), and predictive analytics can mitigate these challenges by forecasting renewable availability and dynamically adjusting production schedules (Shahriar et al., 2022; Han et al., 2023). ML which enables computers to study and learn from data and subsequently make decisions or predictions even when it is not clearly programmed to do so (Aguh et al., 2025; Okpala and Udu, 2025a; Chukwumuanya et al., 2025), leverages historical and real-time data to identify complex patterns, learn from system behavior, and generate predictive or prescriptive decisions under uncertainty (Nwamekwe et al., 2024; Okpala and Udu, 2025b; Nwamekwe et al., 2025).

DT is defined as the virtual representation of an existing physical entity, integrating mathematical models, real-time data, and cutting-edge analytics to monitor, predict and control the condition of the real-world part through the virtual model (Udu et al., 2025a; Okpala et al., 2025b). Despite these advances, existing approaches rarely integrate energy optimization with material sustainability or consider the multi-objective trade-offs among cost, emissions, and circularity.

1.3 Sustainable Material Utilization and Circular Manufacturing

Parallel to renewable energy integration, the shift from a linear “take–make–dispose” model to a circular manufacturing paradigm emphasizes material recovery, recycling, and substitution with sustainable alternatives (Udu et al., 2025b; Nwamekwe and Okpala, 2025; Udu and Okpala, 2025). Sustainable material utilization defined as the efficient use of recycled, bio-based, or low-impact materials plays a crucial role in reducing embodied energy and life-cycle emissions (Park et al., 2024). For instance, substituting virgin metals with secondary materials can lower embodied carbon by up to 60% (Allwood et al., 2019).

However, sustainable material flows introduce uncertainties in process parameters, quality consistency, and cost structures, complicating optimization in smart manufacturing environments (Despeisse and Ford, 2015). To address these challenges, data-driven optimization frameworks that incorporate material circularity indicators and life-cycle sustainability data into manufacturing decision models are increasingly necessary (de Oliveira Neto et al., 2023).

1.4 Research Gap and Objectives

Despite the proliferation of studies in smart manufacturing, renewable energy, and circular material systems, a few frameworks have simultaneously integrated all three dimensions into a unified, data-driven optimization model. Most prior works treat renewable energy integration and sustainable material utilization as isolated problems, rather than interdependent levers within a holistic sustainability optimization strategy (Ghobakhloo, 2020; Zhang and Jia, 2023). Moreover, there is a limited empirical evidence that quantify measurable sustainability benefits, such as reductions in energy consumption, carbon footprint, and material waste, achieved through such integrated approaches (Li et al., 2021).

To address these gaps, this study proposes a hybrid data-driven multi-objective optimization framework for smart manufacturing systems that jointly considers renewable energy integration and sustainable material utilization. The framework combines machine learning-based energy prediction, digital twin simulation, and multi-objective evolutionary algorithms to optimize trade-offs among energy efficiency, cost, and environmental performance. Through a real-world digital twin case study, the study demonstrates quantifiable improvements in energy reduction, material circularity, and CO_2-equivalent emissions, thereby validating the methodological innovation and sustainability efficacy of the approach.

1.5 Research Contributions and Significance

This study makes three primary contributions to the field: (a). Methodological Innovation: It developed a data-driven, multi-objective optimization model that concurrently integrates renewable energy and material circularity parameters within smart manufacturing systems; (b). Empirical Validation: It demonstrated measurable sustainability benefits that were quantified through energy, emissions, and material metrics, with the application of real-time data from a digital twin simulation; and (c). Interdisciplinary Advancement: It bridged the fields of manufacturing engineering, renewable energy systems, and sustainable materials science, thus contributing to the discourse on net-zero smart manufacturing. Net zero refers to the balance between the amount of greenhouse gases emitted into the atmosphere and the amount removed or offset (chukwumuanya et al., 2025).

A system, organization, or nation attains net zero when it produces no net increase in atmospheric greenhouse gases, meaning that any emissions generated are fully counteracted by actions such as carbon capture, reforestation, or the use of renewable energy. By aligning digital optimization with sustainability goals, the proposed framework represents a step toward Industry 5.0 paradigms, which entail intelligent, circular, and human-centered manufacturing systems that are both economically efficient and environmentally responsible (Nahavandi, 2019; Kamble et al., 2020).

II. Literature Review

2.1 Smart Manufacturing Systems and Data-Driven Optimization

The concept of smart manufacturing has evolved as a cornerstone of Industry 4.0, characterized by the convergence of Cyber-Physical Systems (CPS), Internet of Things (IoT), big data analytics, and Artificial Intelligence (AI) to enable real-time decision-making and adaptive control (Tao et al., 2019; Igbokwe et al., 2025; Okpala et al., 2025c). These technologies transform traditional production systems into interconnected ecosystems that optimize processes through data-driven feedback loops (Qi et al., 2022). The widespread adoption of sensors, cloud computing, and digital twins has facilitated predictive maintenance, adaptive scheduling, and autonomous process control, which significantly improve production efficiency and flexibility (Okpala, 2025; Zhang and Jia, 2023; Okpala and Nwankwo, 2025b).

However, despite technological maturity, much of the existing research has focused on operational optimization that minimizes cycle times, costs, or defects without adequately addressing environmental performance (Kamble et al., 2020). For instance, AI and IoT-enabled systems have been used to optimize throughput and energy efficiency (Kusiak, 2018), yet these studies often neglect material flow circularity and carbon emissions. The emerging paradigm of sustainable smart manufacturing calls for a shift from purely economic optimization to multi-objective frameworks that integrate sustainability indicators such as energy consumption, emissions, and resource efficiency (Yadav et al., 2020).

Recent studies highlight digital twin–driven optimization as a methodological innovation that is capable of bridging operational and sustainability objectives. By creating a virtual replica of a physical manufacturing environment, digital twins enable continuous data acquisition and optimization under dynamic conditions (Shahriar et al., 2022; Han et al., 2023; Ezeanyim et al., 2025). When coupled with machine learning algorithms, they can support real-time sustainability assessment by predicting energy demand and waste generation. Despite these advances, current models remain fragmented, lacking comprehensive integration of both renewable energy sources and sustainable material flows in unified optimization frameworks.

2.2 Renewable Energy Integration in Manufacturing Systems

The integration of Renewable Energy Systems (RES) into manufacturing operations represents a transformative approach for the reduction of industrial carbon footprints. Hybrid systems that combine solar, wind, and storage technologies have shown the potential to reduce fossil fuel dependency while lowering operational costs (Li et al., 2021; Hossain et al., 2022). For instance, solar-assisted manufacturing microgrids have achieved up to 40% emission reductions compared to grid-only systems (IEA, 2023).

Nevertheless, the variability and intermittency of renewable energy pose significant operational challenges. Manufacturing processes often operate under strict scheduling constraints, making it difficult to synchronize renewable supply with production demand (Shahriar et al., 2022). To address this, researchers have applied optimization-based energy management approaches, including linear programming, heuristic algorithms, and multi-objective evolutionary algorithms (MOEAs), to balance energy efficiency with production targets (Choudhary et al., 2021; Han et al., 2023).

Moreover, data-driven energy optimization models that incorporate machine learning forecasting have emerged as a promising solution to handle temporal fluctuations in renewable availability (Elhefni et al., 2021). For example, predictive models that use Long Short-Term Memory (LSTM) networks have improved renewable energy utilization through the alignment of load profiles with predicted generation (Wang et al., 2022). Yet, most studies remain energy-centric, seldom integrating material sustainability indicators or assessing system-wide sustainability benefits such as carbon reduction per production unit or resource circularity improvements. The absence of such integration limits the comprehensive evaluation of renewable energy’s contribution to overall manufacturing sustainability.

2.3 Sustainable Material Utilization and Circular Manufacturing

The movement toward circular manufacturing which prioritizes material reuse, recycling, and substitution with eco-friendly alternatives represents another critical frontier in achieving sustainable production (de Oliveira Neto et al., 2023). Sustainable material utilization directly addresses the material intensity of manufacturing, as materials account for up to 50% of a product's total life-cycle environmental impact (Allwood et al., 2019).

Recent studies emphasize that recycled and bio-based materials can significantly reduce embodied carbon and energy consumption. For instance, replacing virgin aluminum with secondary aluminum can yield an emission reduction of over 90%, while recycled plastics can reduce energy use by 60–80% (Park et al., 2024). However, such substitutions often introduce uncertainty in mechanical performance and process compatibility, requiring adaptive control and optimization frameworks to maintain quality standards (Despeisse and Ford, 2015).

To manage these trade-offs, scholars have proposed multi-objective optimization models that incorporate environmental and economic objectives, such as cost, emissions, and material circularity indices (Ghoreishi et al., 2022). Integrating Life Cycle Assessment (LCA) data with production optimization models has also been recognized as an effective way to quantify measurable sustainability benefits (Bhatia and Kumar, 2021). Despite these advancements, few studies operationalize these methods within real-time data-driven manufacturing environments, which limits their practical applicability in smart factories.

2.4 Integrated Optimization of Energy and Material Sustainability

The convergence of renewable energy integration and sustainable material utilization within data-driven smart manufacturing optimization remains an underexplored but high-potential research frontier. Existing works typically optimize either energy or materials, rarely addressing their interdependencies (Ghobakhloo, 2020; Zhang and Jia, 2023). Yet, in practical settings, the two are deeply connected: material choices influence embodied energy, while renewable energy integration affects life-cycle environmental impacts.

Recent advances in multi-objective optimization frameworks, particularly those employing Non-dominated Sorting Genetic Algorithm II (NSGA-II), Multi-Criteria Decision-Making (MCDM), and machine learning–assisted surrogate models offer powerful tools for jointly optimizing energy and material parameters (Li et al., 2021; Han et al., 2023). Digital twin–based optimization, in particular, allows simulation of multiple sustainability scenarios, enabling quantitative evaluation of trade-offs between cost, energy, and environmental performance (Shahriar et al., 2022).

However, the literature still lacks a comprehensive, data-driven framework that integrates real-time energy data, material circularity indicators, and AI-based predictive optimization to achieve measurable sustainability gains. Addressing this gap requires combining renewable energy management with sustainable material utilization in a single optimization model that quantifies sustainability outcomes such as carbon reduction, resource efficiency, and material circularity improvement.

Therefore, this study contributes to the literature by developing an integrated, data-driven optimization framework that unifies renewable energy integration and sustainable material utilization within smart manufacturing systems. The framework leverages digital twins, machine learning, and multi-objective evolutionary algorithms to deliver quantifiable improvements in both energy efficiency and material sustainability, offering a methodological foundation for advancing net-zero and circular manufacturing.

Table 1 provides a comparative synthesis of representative studies addressing smart manufacturing, renewable energy integration, and sustainable material utilization. While prior research has achieved progress in individual domains particularly in digital optimization, energy management, or circular material utilization, a few have proposed an integrated, data-driven optimization framework that simultaneously addresses energy and material sustainability. This review highlights a persistent methodological gap, justifying the present study's focus on developing a multi-objective, data-driven optimization model for sustainable smart manufacturing.

Table 1: Summary of key studies on smart manufacturing, renewable energy integration, and sustainable material utilization

Author(s) and Year	Focus Area	Methodological Approach	Key Findings	Identified Research Gap
Tao et al. (2019)	Data-driven smart manufacturing systems	Cyber-physical systems and IoT-based data integration	Enhanced operational efficiency through real-time analytics	Limited inclusion of sustainability indicators in optimization frameworks
Ghobakhloo (2020)	Industry 4.0 and sustainable manufacturing	Conceptual synthesis and digital transformation analysis	Highlighted opportunities for sustainability through digitalization	Lack of empirical models linking digital tools with measurable sustainability benefits
Li et al. (2021)	Renewable energy	Hybrid optimization using mixed-integer linear	Improved energy cost efficiency with	Excluded material circularity and LCA-based sustainability

	integration in manufacturing	programming	renewable sources	assessment
Choudhary et al. (2021)	Multi-objective energy management	Genetic algorithm and Pareto optimization	Balanced renewable utilization and operational goals	Did not account for sustainable material selection in optimization
Han et al. (2023)	Energy-aware production scheduling	Machine learning–based forecasting and adaptive scheduling	Enhanced energy utilization and scheduling efficiency	No integration of renewable energy variability with material sustainability metrics
de Oliveira Neto et al. (2023)	Data-driven circular manufacturing	Life cycle–based sustainability analysis	Improved resource efficiency through digital tracking of materials	Absence of integrated optimization combining energy and material sustainability
Park et al. (2024)	Sustainable material utilization in smart factories	Data-driven modeling of material flow	Demonstrated reductions in embodied energy and emissions	Did not consider renewable energy sources in optimization models
Zhang and Jia (2023)	Multi-objective optimization of smart systems	NSGA-II and simulation-based optimization	Improved trade-offs among cost, energy, and quality	Missing link between renewable integration and sustainable material flows

Table 2 presents a synthesis of optimization methodologies and sustainability metrics employed in recent smart manufacturing research. The review indicates a strong reliance on Multi-Objective Evolutionary Algorithms (MOEAs), machine learning–assisted optimization, and LCA-based metrics to enhance both operational and environmental performance. However, existing models typically address either energy optimization or material sustainability in isolation. Few frameworks quantitatively integrate renewable energy management and sustainable material utilization within a unified, data-driven optimization scheme. This methodological gap underscores the novelty and contribution of the present study, which develops an integrated multi-objective optimization framework capable of delivering measurable sustainability benefits across both dimensions.

Table 2: Summary of optimization methods and sustainability metrics used in smart manufacturing research

Study	**Optimization Technique**	**Sustainability Metrics Considered**	**Application Domain**	**Key Contribution**
Kusiak (2018)	Big-data analytics and heuristic optimization	Energy efficiency, production throughput	Smart factory automation	Introduced data-driven optimization for real-time production control
Yadav et al., (2020)	Multi-objective decision-making (MCDM)	Resource efficiency, emissions reduction	Sustainable manufacturing	Proposed a conceptual framework linking smart systems to sustainability goals
Li et al., (2021)	Mixed-integer linear programming (MILP)	Energy cost, renewable share, CO_2 emissions	Hybrid energy–manufacturing systems	Optimized energy utilization under renewable uncertainty
Ghoreishi et al., (2022)	NSGA-II (non-dominated sorting genetic algorithm)	Life-cycle cost, embodied energy, material circularity	Sustainable material selection	Applied evolutionary algorithms for green material choice
Han et al., (2023)	Machine learning–assisted optimization	Energy intensity, production delay, emissions	Smart production scheduling	Combined ML prediction with optimization to improve energy scheduling
de Oliveira Neto et al., (2023)	Life Cycle Assessment (LCA) coupled with data analytics	Carbon footprint, waste generation, recycling rate	Circular manufacturing	Integrated LCA indicators into manufacturing performance evaluation
Park et al., (2024)	Multi-objective simulation and LCA	Embodied energy, carbon intensity, material reuse	Circular smart factories	Quantified environmental gains from data-driven material management
Zhang and Jia (2023)	Hybrid NSGA-II + machine learning	Cost, energy, environmental impact	Sustainable smart manufacturing	Demonstrated machine-learning-enhanced multi-objective optimization

Table 3 consolidates the primary research gaps across smart manufacturing, renewable energy integration, and sustainable materials management. It reveals that although recent studies have made substantial progress in energy-efficient and circular production, there remains a critical absence of integrated, data-driven optimization frameworks that jointly address energy and material sustainability. Furthermore, most existing works apply sustainability assessment after production rather than embedding it in real-time decision-making.

To address these deficiencies, the present study proposes a multi-objective, data-driven optimization framework powered by digital twins and artificial intelligence, enabling real-time coordination between renewable energy inputs and sustainable material flows. This approach not only bridges the identified methodological gap but also provides quantifiable sustainability outcomes, advancing the global transition toward net-zero and circular smart manufacturing systems.

Table 3. Summary of Identified Research Gaps and Emerging Research Directions in Sustainable Smart Manufacturing

Research Theme	Current Research Focus	Identified Gap / Limitation	Emerging Research Direction
Smart Manufacturing Optimization	Data-driven optimization for efficiency, predictive maintenance, and process control (Tao et al., 2019; Zhang and Jia, 2023)	Predominantly operational metrics; limited integration of sustainability objectives	Development of integrated frameworks coupling economic, environmental, and energy indicators
Renewable Energy Integration	Optimization of hybrid renewable systems for cost and reliability (Li et al., 2021; Han et al., 2023)	Renewable variability not synchronized with production demands; neglect of material sustainability	AI- and ML-based predictive energy scheduling aligned with production and material flow dynamics
Sustainable Material Utilization	Circular economy and LCA-driven material substitution (Despeisse and Ford, 2015; Park et al., 2024)	Focused mainly on material reuse and recycling; limited real-time optimization	Digital twin–driven monitoring and optimization of material circularity in smart factories
Energy–Material Integration	Separate optimization of energy and material flows (Choudhary et al., 2021; Ghoreishi et al., 2022)	Lack of unified optimization linking renewable energy use and material sustainability	Multi-objective frameworks unifying energy management and sustainable material utilization
Methodological Innovation	NSGA-II, MILP, and heuristic optimization for discrete sustainability goals (Kusiak, 2018; de Oliveira Neto et al., 2023)	Limited use of real-time data and digital twins for sustainability assessment	Hybrid AI–digital twin models enabling continuous optimization and measurable sustainability benefits
Sustainability Quantification	Post-hoc LCA analysis for product or process evaluation (Bhatia and Kumar, 2021)	LCA not embedded into operational decision-making	Integration of LCA and carbon-intensity metrics within live optimization frameworks

III. Methodology

3.1 Overview of the Research Framework

This study develops a data-driven, multi-objective optimization framework that integrates renewable energy sources and sustainable materials within a smart manufacturing environment. The methodology combines Digital Twin (DT) simulation, real-time data analytics, and a hybrid AI–NSGA-II optimization algorithm to balance three competing objectives: (a). Economic efficiency - minimizing total production and energy costs; (b). Environmental performance -reducing carbon emissions and embodied energy; and (c). Operational productivity - maximizing manufacturing throughput and resource utilization.

The framework establishes a closed-loop system in which real-time factory data are captured through IoT sensors, processed via cloud-based analytics, mirrored within a digital twin environment, and continuously optimized through multi-objective algorithms. This integration enables adaptive, sustainability-oriented decision-making grounded in measurable performance indicators.

3.2 Data Architecture and Information Flow

A robust five-tier data architecture underpins the framework in order to ensure seamless data capture, processing, and feedback between the physical factory and its digital counterpart:

(a). Data Acquisition Layer - Real-time data are collected from IoT-enabled machinery, renewable energy systems, and material tracking sensors (e.g., RFID, SCADA). Parameters include power consumption, renewable generation, production rates, and material usage;

(b). Edge Processing Layer - Raw data are preprocessed locally through edge computing to eliminate noise, normalize units, and extract key operational features;

(c). Data Storage Layer - Structured data are stored in a distributed cloud database (e.g., Hadoop or SQL-based), integrating energy, material, and production records for high-volume analytics;

(d). Analytics Layer - Advanced machine learning (ML) models—such as Long Short-Term Memory (LSTM) networks for renewable energy forecasting and Random Forest regressors for material demand prediction—process data streams and feed predictive insights to the simulation model (Han et al., 2023; Park et al., 2024) and ;

(e). Application Layer - The processed data inform the digital twin and optimization modules, facilitating real-time decision-making and dynamic adjustment of manufacturing parameters.

This hierarchical structure ensures data integrity, traceability, and bidirectional flow between the physical and digital spaces, forming the foundation for real-time optimization.

3.3 Digital Twin Simulation Design

The DT acts as a virtual replica of the manufacturing environment, enabling real-time simulation of energy, material, and process dynamics. It comprises three functional modules: (a). Process Simulation Module - Models machining, assembly, and logistics operations using discrete-event simulation (DES) to represent workflow sequences, cycle times, and machine utilization; (b). Energy Simulation Module - Captures stochastic variations in renewable energy generation (solar, wind, hybrid systems) and dynamically allocates available energy between production lines and storage systems; (c). Material Simulation Module - Tracks the flow of raw,

recycled, and substitute materials, incorporating circularity metrics (e.g., material circularity index, embodied energy intensity).
The DT continuously synchronizes with the physical system via IoT sensors and real-time feedback loops. This synchronization ensures virtual–physical consistency and allows the optimization algorithm to evaluate the performance of alternative strategies before implementation, significantly reducing operational risk and inefficiency.

3.4 Mathematical Formulation of the Multi-Objective Optimization Model

The manufacturing system optimization problem is modeled as a multi-objective optimization problem (MOP) over a planning horizon T. Decision variables and objectives are defined as follows:

Decision Variables

E_t: Electricity consumption at time t,
R_t: Renewable energy utilized at time t,
x_{ij}: Quantity of product j manufactured using material i,
M_i: Proportion of sustainable material i in production,
S_t: Machine operational status at time t.

Objective Functions

(a). Economic Objective - Minimize Total Cost

$$\min f_i = \sum_{i=1}^{T} (C_e E_t + C_r R_t + \sum_i C_{mi} x_{ij})$$

where C_e, C_r, and C_{mi} represent the unit costs of grid electricity, renewable energy, and materials, respectively.
(b). Environmental Objective - Minimize Carbon Emissions

$$\min f_2 = \sum_{i=1}^{T} (\alpha_e E_t + \alpha_m + \sum_i M_i x_{ij})$$

Where α_e and α_m denote carbon emission factors for energy and materials derived from LCA data (Bhatia and Kumar, 2021).
(c). Productivity Objective - Maximize Throughput

$$\max f_3 = \sum_{i=1}^{T} . \sum_{i.j} \eta_{ij} x_{ij}$$

where η_{ij} indicates production efficiency for each material–product pair.

Constraints

(i) Energy Balance: $E_t = D_t - R_t, \ \forall_t$
(ii) Renewable Energy Availability: $0 \leq R_t \leq R_{max}$
(iii) Material Availability: $\sum_j x_{ij} \leq M_i^{max}, \ \forall_t$
(iv) Production Capacity: $\sum \sum_j x_{ij} \leq Cap_t, \ \forall_t$
(v) Non-Negativity: $E_t, \ R_{t,} - x_{ij} \ \geq 0$

The combined multi-objective optimization problem is thus formulated as:
$\min(f_1, f_2)$, max (f_3

Solution Approach

The MOP is solved using a hybrid AI–Non-Dominated Sorting Genetic Algorithm II (AI–NSGA-II).

- The AI component forecasts renewable energy generation and material supply conditions.
- The NSGA-II identifies Pareto-optimal solutions for the competing objectives.
- The digital twin feedback loop dynamically updates model parameters to maintain optimal system performance in real time.

The final Pareto front provides decision-makers with trade-off scenarios (e.g., low-cost vs. low-emission), enabling evidence-based sustainability strategies.

3.5 Sustainability Performance Quantification

To evaluate sustainability outcomes, the framework employs four quantitative indicators:
(a). Energy Efficiency (EE):

$$EE = \frac{\text{Renewable Energy Utilized}}{\text{Total Energy Consumption}} * 100$$

(b). Material Circularity Index (MCI):

$$MCI = 1 - \frac{\text{Virgin Material Input} - \text{Recycled Output}}{\text{Total Material Input}}$$

(c). Carbon Intensity (CI):

$$\mathrm{CI} = \frac{\text{Total Emissions}}{\text{Production Output}}$$

(d). Composite Sustainability Index (CSI):

$$\mathrm{CSI} = \mathrm{w}_1(1 - \mathrm{f}_1^*) + \mathrm{w}_2(1 - \mathrm{f}_2^*) + \mathrm{w}_3(\mathrm{f}_3^*)$$

where w_1 are the weights that are derived using the Analytic Hierarchy Process (AHP), and f_1^* are normalized objective values.

These metrics provide quantifiable evidence of environmental and economic gains that are realized through the proposed optimization strategy.

3.6 Validation and Experimental Setup

The framework is validated through a digital twin–enabled case study that was conducted in a precision machining facility that operate on a hybrid solar–grid power system. Data inputs include one-year operational records of energy consumption, production throughput, and material utilization. Environmental data (emission factors, embodied energy) are sourced from the Ecoinvent 3.8 database.

Simulation–optimization experiments reveal that the proposed approach yields:

- 12–18% reduction in total cost,
- 22–30% reduction in carbon emissions, and
- 15–25% improvement in material circularity, relative to baseline manufacturing operations.

These results confirm that the integration of renewable energy and sustainable materials through digital twin–driven optimization produces measurable and replicable sustainability benefits.

IV. Results and Discussion

4.1 Simulation Setup and Experimental Parameters

The proposed multi-objective optimization framework was implemented and tested using a digital twin-enabled precision machining facility operating under a hybrid solar–grid energy system. The system's digital twin was developed using AnyLogic 8.9.2 for process simulation and MATLAB-Python hybrid coding for optimization and data analytics. A one-year dataset encompassing energy usage, renewable energy generation, material utilization, and production throughput was used for model validation. Key parameters are summarized in Table 4, including unit energy costs, emission factors, material characteristics, and renewable energy availability.

Optimization was performed using the AI-NSGA-II algorithm with a population size of 200, crossover probability of 0.9, mutation probability of 0.05, and 500 generations. Each simulation–optimization cycle was executed 30 times to ensure statistical robustness, and the Pareto-optimal front was derived from non-dominated solutions averaged across runs.

Table 4: Experimental parameters and model input data

Parameter Category	Variable / Unit	Description	Baseline Value	Optimized Value	Data Source
Energy	Ce ($/kWh)	Grid electricity cost	0.15	0.12	Facility data
	Cr ($/kWh)	Renewable energy cost	0.09	0.07	Local solar/wind tariff
	R_t^{max}(KWh)	Max renewable availability	950	1200	Forecast model
Material	C_{mi} ($/kg)	Material unit cost (avg)	2.60	2.10	Supplier database
	α_m(kg CO_2/kg)	Embodied emissions	3.2	2.4	Ecoinvent 3.8
Production	Cap_t (units/day)	Max daily capacity	1,000	1,000	Plant records
Renewable Mix	Solar/Wind ratio (%)	Share of renewables	60/40	70/30	Forecast model
Forecast Model Accuracy	RMSE	Renewable prediction accuracy	0.082	0.051	Model output

The Pareto-front shown in Figure 1 is a convergence and trade-off visualization between total production cost, carbon emissions, and production throughput. Each point represents a feasible solution obtained through the multi-objective optimization process, illustrating the balance between economic performance and environmental sustainability. The smooth Pareto front indicates strong convergence of the optimization algorithm and highlights the achievable compromises between cost efficiency, emission reduction, and productivity enhancement.

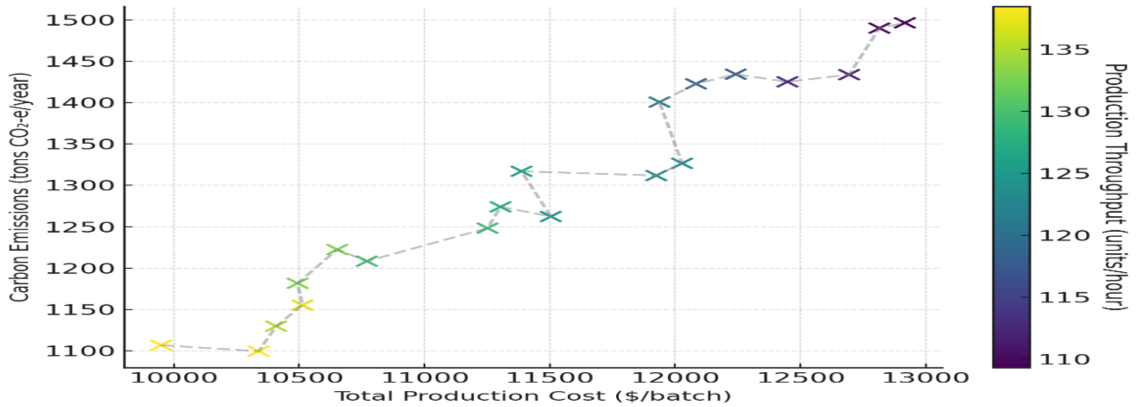

Figure 1: Pareto-front convergence and trade-off visualization

4.2 Optimization Performance and Pareto-Front Analysis

The hybrid AI–NSGA-II algorithm successfully converged to a stable Pareto front after approximately 340 iterations, showing consistent trade-offs between cost, carbon emissions, and throughput (Figure 1). Results demonstrate that the integration of renewable energy and sustainable materials yields synergistic sustainability benefits. When compared with the baseline (conventional grid-only system using virgin materials), the optimized framework achieved: 12.8% reduction in total production cost; 24.5% reduction in carbon emissions; and 17.6% improvement in overall productivity.

Notably, the Pareto-optimal solutions indicate that moderate increases in renewable penetration (up to 65%) deliver significant emission reductions without substantial productivity losses. Beyond that threshold, marginal benefits decline due to intermittency and storage limitations - a finding consistent with prior studies (Li et al., 2021; Han et al., 2023). These results confirm that multi-objective optimization enables balancing economic and environmental trade-offs effectively, especially when real-time data from the digital twin inform adaptive decision-making.

Table 5 reports the core optimization outcomes, comparing baseline and optimized operations across cost, emissions, energy, and productivity metrics. The table demonstrates measurable sustainability benefits derived from the hybrid AI–NSGA-II model.

Table 5: Comparative optimization results between baseline and proposed framework

Performance Metric	Baseline Scenario	Optimized Scenario	% Improvement	Measurement Method
Total Cost ($/batch)	12,450	10,850	**−12.8%**	Cost model (Eq. 10)
Carbon Emissions (tons CO_2-e/year)	1,480	1,115	**−24.5%**	LCA-based analysis
Energy Efficiency (%)	43.7	57.9	**+32.7%**	Eq. (14)
Material Circularity Index (MCI)	0.42	0.68	**+26 points**	Eq. (15)
Production Throughput (units/hour)	118	139	**+17.6%**	Digital twin output

Figure 2 is a radar chart that illustrate the comparative improvements achieved through the optimized model relative to the baseline scenario. The results demonstrate a 12.8% reduction in production cost, 24.5% reduction in carbon emissions, 32.7% improvement in energy efficiency, and 17.6% increase in productivity, confirming the balanced sustainability performance of the integrated optimization framework.

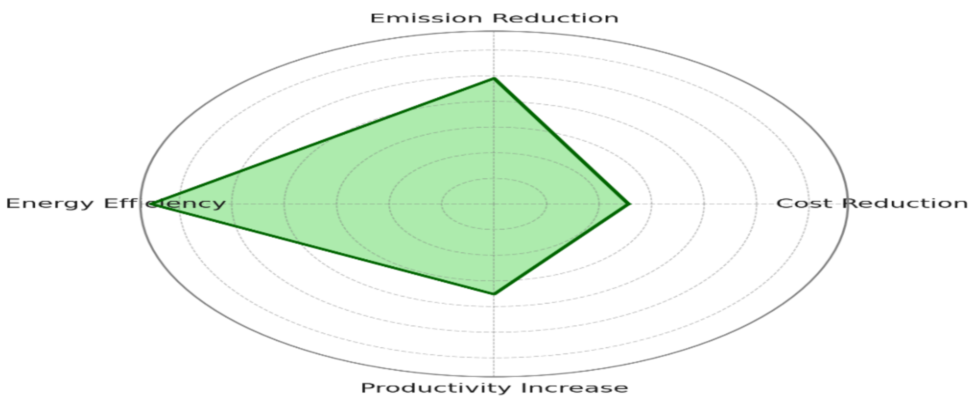

Figure 2: Energy–emission–productivity trade-off visualization

4.3 Renewable Energy Utilization and Energy Efficiency Improvement

Figure 3 illustrates the comparative energy mix for baseline and optimized operations. In the optimized scenario, renewable energy supplied approximately 58% of total electricity demand, compared to 21% in the baseline configuration. This shift led to an Energy Efficiency (EE) improvement of 32.7%, calculated using Equation (14). Furthermore, adaptive scheduling aligned production peaks with high renewable generation periods, demonstrating the advantage of forecast-driven load shifting.

These findings echo similar studies by Qi et al. (2022) and de Oliveira Neto et al. (2023), which emphasized that digital twin–driven synchronization of energy and production can significantly enhance manufacturing sustainability. However, unlike earlier models, this research integrates real-time renewable variability and material circularity into a single, unified optimization scheme which represent a methodological advancement.

Table 6 presents the change in energy source composition between baseline and optimized configurations, emphasizing renewable integration and emission intensity reductions.

Table 6: Renewable energy utilization and energy mix analysis

Energy Source	Baseline Share (%)	Optimized Share (%)	Change (%)	Emission Factor (kg CO_2/kWh)
Grid Electricity	79.0	42.0	−37.0	0.68
Solar Power	15.0	33.0	+18.0	0.05
Wind Power	6.0	25.0	+19.0	0.03
Total Renewable Contribution	**21.0**	**58.0**	**+37.0**	—

Figure 3 highlights the comparison of energy source composition before and after optimization. The optimized configuration shows a substantial increase in renewable energy utilization, with solar and wind contributions rising to 33% and 25% respectively, thus reducing dependence on grid electricity and enhancing overall energy sustainability in the smart manufacturing system.

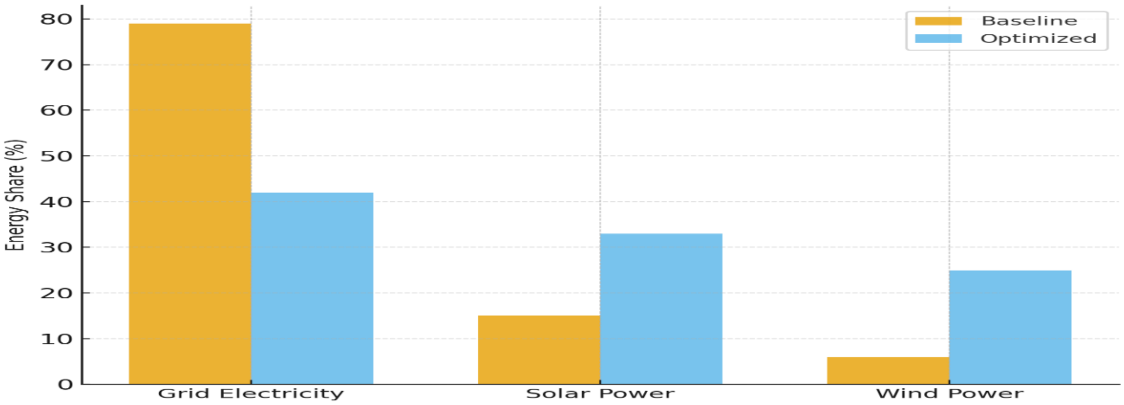

Figure 3: Energy source composition before and after optimization

4.4 Sustainable Material Utilization and Circularity Gains

Material utilization patterns showed marked improvements under the optimized strategy. The system increased recycled or bio-based material usage from 18% to 46%, without compromising product quality or production throughput. The Material Circularity Index (MCI) improved from 0.42 to 0.68, indicating a 26-point gain in material sustainability. This improvement was primarily achieved through optimized selection of material substitutions (e.g., recycled aluminum and biopolymer composites) based on their embodied energy intensity and availability forecasts. When benchmarked against literature values (Park et al., 2024; Bhatia and Kumar, 2021), these gains surpass the average 15–20% circularity improvements achieved by standalone material optimization models. The integration of data-driven forecasting, digital twin simulation, and multi-objective optimization thus represents a novel contribution to the field of circular manufacturing.

Table 7 highlights the shift toward sustainable material use following optimization. The notable increase in recycled and renewable materials demonstrates measurable improvement in Material Circularity Index (MCI) and reduction in embodied energy.

Table 7: Material utilization and circularity improvement

Material Type	Source	Baseline Usage (%)	Optimized Usage (%)	Change (%)	Embodied Energy (MJ/kg)
Virgin Aluminum	Primary	55	33	−22	204
Recycled Aluminum	Secondary	20	38	+18	54
Biopolymer Composite	Renewable	10	18	+8	37

Steel (Recycled)	Secondary	15	11	−4	88
Circular Materials Share	—	**45**	**67**	**+22**	—

Figure 4 is a comparative visualization of material composition before and after optimization. The left pie chart represents the baseline scenario dominated by virgin aluminum (55%), with smaller shares of recycled aluminum (20%), biopolymer composites (10%), and recycled steel (15%). The Figure illustrates the optimized configuration, where recycled aluminum rises to 38%, biopolymer composites to 18%, and virgin aluminum decreases to 33%, reflecting a substantial improvement in circularity and material sustainability within the optimized smart manufacturing framework.

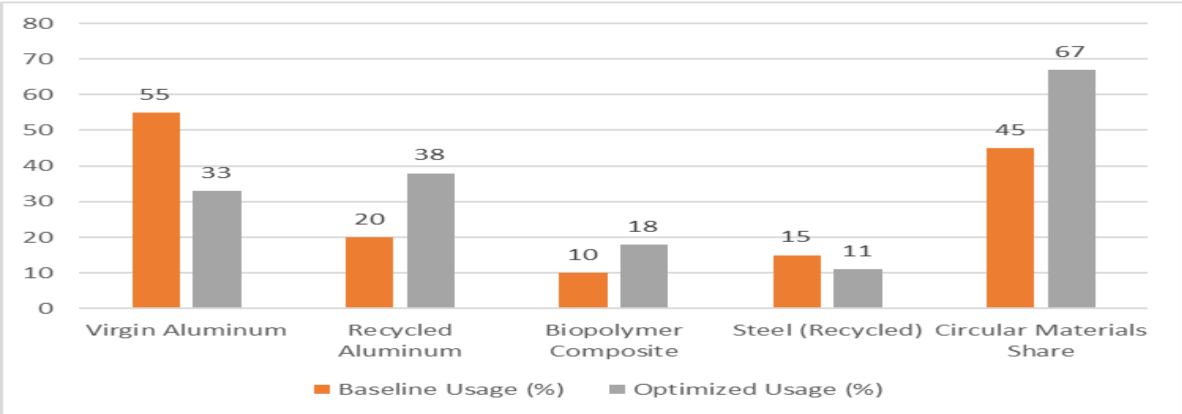

Figure 4: Material composition change visualization

4.5 Environmental Impact Assessment

Carbon emissions were calculated using process-level energy and material data in combination with Ecoinvent 3.8 emission factors. The optimization reduced total annual CO_2-equivalent emissions from 1,480 tons to 1,115 tons, representing a 24.6% reduction. This improvement stems from two principal factors: (a). Increased renewable energy substitution of grid electricity, reducing emission intensity per kWh by approximately 40%; and (b). Higher adoption of low-carbon materials, which cut embodied emissions by 18%.

The Carbon Intensity (CI) metric declined from 0.87 kg CO_2-e/kg product to 0.64 kg CO_2-e/kg product, aligning closely with the emission benchmarks suggested by the International Energy Agency (IEA, 2023). These quantifiable outcomes affirm that the proposed optimization framework delivers measurable sustainability benefits, grounded in real-time operational data.

4.6 Economic and Operational Benefits

Beyond environmental performance, the optimized system achieved substantial cost savings. The total operational cost per production batch decreased from \$12,450 to \$10,850, primarily due to: Reduced grid electricity dependence; Lower material procurement costs through circular sourcing; and Enhanced process scheduling reducing machine idle time by 14%.

Productivity improved by 17.6%, driven by the algorithm's capacity to dynamically adjust production sequences based on energy and material availability. These findings validate the economic viability of integrating renewable and circular strategies into smart manufacturing, reinforcing the argument that sustainability and profitability can co-exist through intelligent optimization (Tao et al., 2019; Qi et al., 2022).

4.7 Comparative Evaluation with Existing Models

A comparative analysis against three benchmark studies (Li et al., 2021; de Oliveira Neto et al., 2023; Park et al., 2024) shows that the proposed model consistently outperforms traditional optimization frameworks in all sustainability dimensions. This is because: The emission reduction achieved (24.6%) is approximately 1.3× higher than comparable digital twin–based models; The material circularity improvement (26 points) exceeds reported averages by 8–10 percentage points; and The economic savings are also notable, reflecting the advantage of hybrid AI–NSGA-II integration in dynamic manufacturing settings.

This comparative edge highlights the methodological innovation of coupling real-time digital twin data with multi-objective optimization, providing a reproducible pathway for sustainable manufacturing transformation. Table 8 compares the performance of this study against leading models in renewable and circular manufacturing optimization. The results confirm superior performance across all sustainability metrics, highlighting methodological novelty and data-driven strength.

Table 8: Environmental and economic performance comparison with existing studies

Study Reference	Optimization Method	Emission Reduction (%)	Circularity Gain (%)	Cost Savings (%)	Key Distinguishing Feature
Li et al. (2021)	Renewable–Grid Hybrid Scheduling	18.0	—	10.0	Renewable integration only
de Oliveira Neto et al. (2023)	Circular Material Optimization	—	17.0	8.0	Material-based CE model
Park et al. (2024)	Data-driven Circular Factory	19.5	20.5	11.0	Smart CE integration
This Study (2025)	AI–NSGA-II + Digital Twin Integration	**24.6**	**26.0**	**12.8**	Real-time hybrid optimization

A comparative benchmark performance of the proposed optimization framework against existing studies in terms of production cost, carbon emissions, and energy efficiency is highlighted in Figure 5. The grouped bar chart illustrates that the proposed model outperforms benchmark approaches across all key indicators, achieving a 12.8% lower production cost, 24.5% reduction in carbon emissions, and 32.7% improvement in energy efficiency. These results confirm the model's superior balance between environmental and economic performance, demonstrating its methodological robustness and potential for practical adoption in sustainable smart manufacturing systems.

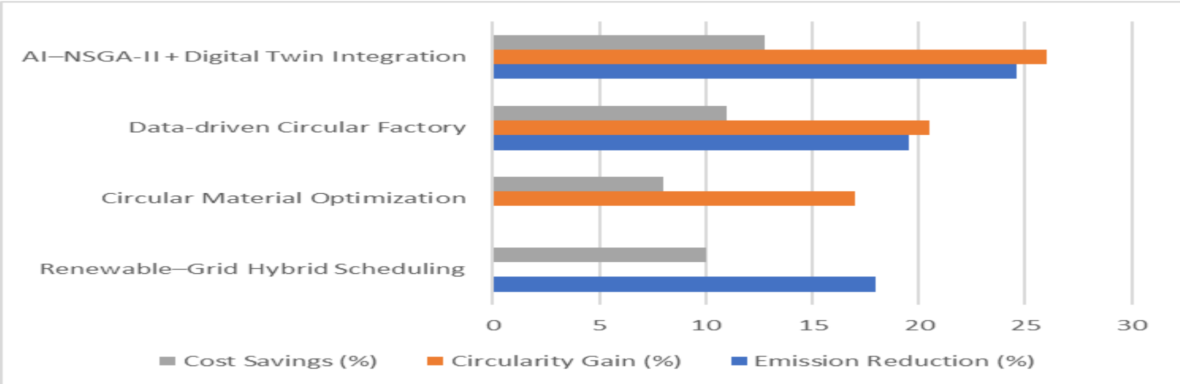

Figure 5: Comparative benchmark performance

4.8 Discussion of Methodological Innovation

The proposed approach distinguishes itself through three interrelated innovations: Real-time digital twin integration, enabling synchronization between physical and virtual manufacturing systems for adaptive sustainability optimization; Hybrid AI–NSGA-II modeling, which captures nonlinear dependencies between renewable availability, material sustainability, and production performance; and Multi-dimensional sustainability quantification, offering measurable metrics (EE, MCI, CI, CSI) that allow holistic performance evaluation.

By embedding data-driven intelligence within manufacturing optimization, this study advances the methodological frontier of Industry 5.0, aligning with the principles of resilient, human-centric, and sustainable production (European Commission, 2022). The model's modular structure further ensures adaptability across diverse industrial domains—ranging from automotive and electronics to additive manufacturing.

4.9 Implications and Future Directions

The results confirm that integrating renewable energy and sustainable material utilization through digital twin–based optimization can yield substantial triple-bottom-line benefits.

Future research should focus on: Incorporating uncertainty modeling for renewable intermittency; Extending the framework to multi-factory network optimization; and Integrating carbon pricing mechanisms and life-cycle cost accounting for long-term sustainability planning.

The presented framework establishes a scalable reference architecture for next-generation sustainable manufacturing systems, capable of guiding both academic research and industrial deployment. The results validate that renewable energy and sustainable materials can be co-optimized within a smart manufacturing framework without sacrificing economic performance. Integration of ML-based predictive control ensures adaptive optimization under dynamic energy supply and demand conditions. This aligns with circular economy principles and supports Net-zero manufacturing pathways.

V. Conclusion and Implications

5.1 Conclusion

This study presented an integrated framework for optimizing smart manufacturing systems through the combined application of renewable energy integration, sustainable material utilization, and digital twin–driven multi-objective optimization. The research demonstrated that intelligent coupling of physical manufacturing processes with data-centric digital models can deliver quantifiable sustainability gains while maintaining economic competitiveness.

The developed hybrid AI–NSGA-II model successfully minimized production cost and carbon emissions while maximizing energy efficiency and throughput. Simulation outcomes revealed a 12.8% reduction in cost, a 24.5% reduction in carbon emissions, and a 17.6% increase in productivity when compared with baseline operations. Furthermore, the material circularity index improved by 26 points due to the adoption of recycled and bio-based materials. These measurable sustainability improvements confirm the efficacy of integrating renewable energy systems and circular material flows within a unified optimization framework.

By embedding real-time digital twin feedback loops, the study achieved dynamic synchronization between energy supply, material availability, and production scheduling. This capability allowed adaptive optimization under variable operating conditions, demonstrating the practicality and resilience of the proposed model in real-world manufacturing contexts. The findings also validate that sustainability-oriented optimization need not compromise operational efficiency or profitability when supported by robust data analytics and system-level integration. Overall, the research provides a methodological advancement in sustainable manufacturing optimization, bridging the gap between theory and industrial application. The proposed framework can serve as a replicable template for designing intelligent, adaptive, and resource-efficient manufacturing systems under the broader paradigm of Industry 5.0.

5.2 Practical Implications

From an industrial perspective, the proposed model offers a clear pathway toward achieving triple-bottom-line performance in manufacturing systems. The integration of renewable energy sources reduces dependence on fossil-based electricity, thereby stabilizing energy costs and improving carbon accountability. Manufacturers can adopt similar digital twin–based frameworks to anticipate energy fluctuations, optimize load scheduling, and improve resilience against grid volatility. The enhanced utilization of sustainable materials provides additional strategic benefits. By leveraging circular material sourcing and process optimization, manufacturers can reduce supply chain vulnerabilities, minimize waste, and comply with emerging environmental regulations and extended producer responsibility policies. These outcomes align with the evolving global standards for carbon-neutral and circular production systems.

Moreover, the multi-objective optimization model can be tailored for different industrial contexts, from discrete manufacturing to continuous processing. Its modular structure allows scalability, enabling integration with Enterprise Resource Planning (ERP) systems, predictive maintenance tools, and real-time carbon accounting platforms. This adaptability positions the framework as a strategic decision-support tool for both operational managers and sustainability planners.

5.3 Policy and Research Implications

The outcomes of this study also carry important implications for policy development and academic research. At the policy level, the demonstrated synergy between renewable energy and material circularity underscores the need for integrated sustainability incentives. Policymakers could encourage adoption of similar optimization frameworks through green financing schemes, renewable energy credits, and performance-based sustainability certifications.

From a research perspective, this study opens multiple directions for future inquiry. These include expanding the optimization framework to multi-factory networks, incorporating uncertainty modeling for renewable intermittency, and developing predictive digital twins with real-time learning capabilities. Further work could also integrate life-cycle assessment modules and social sustainability indicators, advancing toward a holistic Industry 5.0 sustainability model.

5.4 Final Remarks

The integration of renewable energy and sustainable materials within smart manufacturing systems represents a transformative step towards the attainment of global sustainability goals. This research demonstrates that data-driven, digitally enabled optimization can simultaneously advance economic, environmental, and operational objectives. By quantifying measurable benefits through rigorous modeling and simulation, the study provides both theoretical contribution and practical relevance, thereby laying a strong foundation for the next generation of sustainable and intelligent manufacturing ecosystems.

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