

# AI-Integrated Digital Twins for Carbon-Neutral Smart Manufacturing: A Life Cycle Assessment Approach

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## Abstract

The increasing urgency of climate change mitigation has intensified the need for sustainable and carbon-neutral manufacturing systems. While Industry 4.0 technologies have transformed industrial operations through enhanced automation, connectivity, and intelligence, significant challenges remain in integrating operational optimisation with environmental sustainability objectives. This study proposes an AI-integrated digital twin framework designed to support carbon-neutral smart manufacturing through real-time monitoring, predictive analytics, and life cycle assessment (LCA)-based environmental evaluation. The proposed framework combines Internet of Things-enabled data acquisition, digital twin technology, machine learning algorithms, and sustainability assessment tools within a unified decision-support architecture. Artificial intelligence models are employed for predictive maintenance, energy consumption forecasting, and production scheduling optimisation, while the digital twin provides continuous synchronisation between physical manufacturing assets and their virtual counterparts. To evaluate environmental performance, a life cycle assessment framework is integrated into the system to quantify carbon emissions and assess sustainability impacts throughout manufacturing operations. Results from the case study analysis indicate that the proposed framework improves operational efficiency by reducing equipment downtime, optimising energy use, and enhancing production throughput. Furthermore, the integration of AI-driven optimisation and digital twin technologies contributes to significant reductions in carbon emissions and environmental impacts across multiple life cycle categories. The findings demonstrate that the convergence of artificial intelligence, digital twins, and LCA can provide an effective pathway toward carbon-neutral manufacturing by enabling data-driven decision-making and continuous sustainability optimisation. This study adds to the expanding body of literature on Industry 4.0 sustainability by introducing an integrated framework that connects intelligent manufacturing systems with environmental performance management.

**Keywords:** artificial intelligence, digital twin, Industry 4.0, smart manufacturing, carbon-neutral manufacturing, life cycle assessment, sustainability, predictive maintenance, energy optimisation, industrial decarbonisation.

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## 1. INTRODUCTION

### 1.1 Background and Motivation

The manufacturing sector is under increasing pressure to reduce its environmental footprint while maintaining productivity, competitiveness, and operational resilience. Growing concerns regarding climate change, resource depletion, and greenhouse gas emissions have accelerated the global transition toward carbon-neutral industrial systems. Manufacturing activities contribute substantially to energy consumption and carbon emissions throughout product life cycles, making sustainable production a strategic priority for governments, industries, and international organisations. As a result, the pursuit of carbon-neutral manufacturing

has emerged as a central objective within contemporary industrial development agendas.

In response to these challenges, the concept of Industry 4.0 has transformed the manufacturing landscape through the integration of advanced digital technologies, including cyber-physical systems, the Internet of Things, cloud computing, big data analytics, artificial intelligence, and digital twins. Originally introduced as a strategic initiative to enhance the competitiveness of manufacturing systems, Industry 4.0 has evolved into a broader framework that supports intelligent, interconnected, and sustainable production

environments (Kagermann & Wahlster, 2022). The ability of Industry 4.0 technologies to facilitate real-time monitoring, autonomous decision-making, and resource optimisation has positioned them as key enablers of sustainable manufacturing (Jamwal et al., 2021; Ghobakhloo, 2020).

Among these technologies, digital twins have attracted considerable attention due to their capacity to create dynamic virtual representations of physical manufacturing assets, processes, and systems. By continuously synchronising data between physical and virtual environments, digital twins enable manufacturers to simulate operational scenarios, predict system behaviour, and optimise production performance before implementing physical changes. When combined with artificial intelligence, digital twins become powerful decision support tools capable of identifying inefficiencies, forecasting energy consumption, and recommending sustainability-orientated interventions in real time. Consequently, AI-integrated digital twins are increasingly recognised as a promising pathway to achieving carbon-neutral smart manufacturing systems.

## 1.2 Research Problem

Despite significant technological advances, manufacturing organisations continue to face considerable challenges in measuring, monitoring, and reducing carbon emissions across complex production systems. Carbon emissions originate from multiple interconnected sources, including energy consumption, material usage, transportation activities, and production processes. The dynamic nature of manufacturing environments further complicates efforts to quantify environmental impacts accurately and implement effective mitigation strategies.

Traditional sustainability assessment approaches often rely on periodic data collection and retrospective analyses, which limit their ability to support real-time decision-making. While life cycle assessment has become one of the most widely accepted methodologies for evaluating environmental impacts, conventional LCA applications are frequently static and unable to capture continuously changing operational conditions within modern manufacturing systems. As a result, decision-makers may struggle to identify emerging inefficiencies and implement timely corrective actions.

Furthermore, existing sustainability frameworks often treat environmental assessments and operational optimisations as separate activities. This fragmentation restricts the ability of manufacturers to integrate environmental considerations directly into production planning and control processes. Consequently, there remains a need for intelligent frameworks capable of combining real-time operational data, predictive analytics, and environmental impact assessment to support proactive carbon reduction strategies.

## 1.3 Research Objectives

This study seeks to address the aforementioned challenges by proposing an AI-integrated digital twin framework for carbon-neutral smart manufacturing. The framework aims to leverage artificial intelligence algorithms and digital twin technologies to enhance operational visibility, predictive capabilities, and sustainability performance across manufacturing processes.

The first objective is to develop a comprehensive architecture that integrates real-time manufacturing data, digital twin simulations, and AI-based optimisation techniques within a unified decision support environment. Such integration is expected to facilitate continuous monitoring of production activities and enable data-driven interventions that improve resource efficiency and reduce environmental impacts.

The second objective is to evaluate the carbon reduction potential of the proposed framework through a life cycle assessment approach. By incorporating environmental performance indicators into digital twin simulations, the framework seeks to quantify the effects of operational improvements on carbon emissions and overall sustainability outcomes. This approach contributes to bridging the gap between environmental assessment and intelligent manufacturing optimisation.

## 1.4 Research Questions

To achieve these objectives, the study is guided by the following research questions:

**RQ1:** How can AI-enhanced digital twin systems improve sustainability performance within smart manufacturing environments?

This question investigates the extent to which artificial intelligence and digital twin integration can support energy optimisation, resource efficiency, predictive maintenance, and environmentally informed decision-making.

**RQ2:** How much can data-driven optimisation, supported by AI-integrated digital twin technologies, reduce carbon emissions?

This question examines the environmental benefits of implementing intelligent digital twin frameworks and evaluates their effectiveness using life cycle assessment metrics.

## 1.5 Paper Organisation

The remainder of this paper is organised as follows. Section 2 presents a comprehensive review of the literature related to Industry 4.0, artificial intelligence, digital twins, carbon-neutral manufacturing, and life cycle assessment. Section 3 describes the proposed research

methodology, including the development of the AI-integrated digital twin framework and the LCA evaluation approach. Section 4 presents the results and discusses the implications of the findings for sustainable manufacturing practices. Finally, Section 5 summarises the major conclusions, highlights theoretical and practical contributions, identifies study limitations, and outlines directions for future research.

## 2. REVIEW OF RELATED LITERATURE

### 2.1 Industry 4.0 and Smart Manufacturing

The emergence of Industry 4.0 has fundamentally transformed manufacturing systems through the convergence of digital technologies, intelligent automation, and cyber-physical integration. Originally introduced as a strategic initiative to enhance industrial competitiveness, Industry 4.0 encompasses a broad ecosystem of technologies, including the Internet of Things (IoT), cyber-physical systems (CPS), cloud computing, big data analytics, artificial intelligence (AI), additive manufacturing, and digital twins (Kagermann et al., 2013; Frank et al., 2019). These technologies facilitate seamless communication between machines, products, and humans, enabling the development of highly interconnected and autonomous production environments.

Smart manufacturing represents the practical implementation of Industry 4.0 principles within industrial operations. According to Tao et al. (2018), smart manufacturing leverages real-time data acquisition, advanced analytics, and intelligent decision-making to improve productivity, flexibility, and operational efficiency. Unlike traditional manufacturing systems that rely heavily on centralised control structures, smart factories continuously monitor production processes and dynamically adapt to changing operational conditions through decentralised intelligence.

Beyond operational performance, Industry 4.0 has increasingly been associated with sustainability objectives. Researchers argue that digital technologies can significantly improve resource utilisation, reduce waste generation, optimise energy consumption, and enhance environmental performance throughout manufacturing systems (Ghobakhloo, 2020). For example, IoT-enabled sensors provide continuous visibility into energy usage patterns, while advanced analytics identify inefficiencies that may otherwise remain undetected. Similarly, predictive maintenance technologies reduce material waste and equipment downtime by anticipating machine failures before they occur.

However, Industry 4.0 does not automatically guarantee sustainability outcomes. Bonilla et al. (2018) emphasise that digital transformation may also increase energy demand through expanded computational infrastructure and data processing requirements. Consequently, achieving sustainable smart

manufacturing requires the strategic integration of technological innovation with environmental management objectives. This challenge has stimulated growing interest in intelligent systems capable of simultaneously optimising operational efficiency and environmental performance.

### 2.2 Digital Twin Technology

Digital twin technology has emerged as one of the most influential innovations within Industry 4.0. The concept was initially developed to establish a virtual representation of a physical object that remains continuously synchronised with its real-world counterpart throughout its lifecycle (Grieves & Vickers, 2017). Through bidirectional data exchange, digital twins enable real-time monitoring, simulation, prediction, and optimisation of physical systems.

Tao et al. (2019) define a digital twin as a comprehensive cyber-physical model that integrates physical entities, virtual models, data connections, and service applications. The architecture of a digital twin typically consists of three fundamental layers: the physical layer, which includes machines, sensors, and manufacturing equipment; the virtual layer, which contains computational models and simulation environments; and the communication layer, which facilitates continuous data exchange between physical and virtual domains (Negri et al., 2017).

The increasing availability of IoT devices and cloud computing platforms has accelerated the adoption of digital twins across industrial sectors. Within manufacturing systems, digital twins support a wide range of applications, including process monitoring, predictive maintenance, quality control, production scheduling, and energy management (Kritzinger et al., 2018). By replicating production environments in virtual space, manufacturers can evaluate alternative operational scenarios without disrupting actual production processes.

Recent studies have pointed out the potential of digital twins to support sustainability objectives. Zhang et al. (2022) demonstrate that digital twin systems can optimise energy consumption through real-time monitoring and simulation-based decision-making. Similarly, Lu et al. (2020) argue that digital twins facilitate more efficient resource allocation and environmental performance management by providing continuous visibility into manufacturing operations. Despite these advancements, most existing digital twin applications remain focused primarily on operational efficiency rather than comprehensive carbon reduction strategies.

### 2.3 Artificial Intelligence in Manufacturing

Artificial intelligence is now a key part of smart manufacturing systems. Advances in machine learning, deep learning, and predictive analytics have expanded

the ability of manufacturing organisations to extract actionable insights from increasingly large and complex data sets. AI technologies enable automated learning from historical and real-time data, supporting more accurate predictions and informed decision-making across production environments (Wuest et al., 2016).

Machine learning applications in manufacturing are particularly prominent in predictive maintenance, quality inspection, demand forecasting, and process optimisation. Predictive maintenance systems utilise sensor data to identify patterns associated with equipment degradation and potential failures, thereby reducing downtime and maintenance costs (Lee et al., 2018). Similarly, machine learning algorithms can detect subtle deviations in production processes that may affect product quality, enabling corrective actions before defects occur.

Beyond prediction, AI contributes to operational optimisation through advanced decision support systems. AI-driven optimisation techniques can evaluate large numbers of potential production scenarios and identify solutions that balance productivity, cost efficiency, energy consumption, and environmental performance. According to Rai et al. (2021), AI-based decision support systems improve manufacturing agility by enabling rapid responses to changing production conditions and market demands.

The integration of AI with digital twin environments has further enhanced manufacturing intelligence. Within digital twin systems, AI algorithms can continuously analyse operational data, generate predictive insights, and recommend optimisation actions in real time. Such capabilities are particularly valuable for sustainability management because they enable proactive interventions aimed at reducing resource consumption and carbon emissions. Nevertheless, current implementations often prioritise productivity objectives, while environmental optimisation remains a secondary consideration.

## **2.4 Carbon-Neutral Manufacturing**

Carbon-neutral manufacturing refers to production systems that achieve net-zero carbon emissions through a combination of emission reduction, energy efficiency improvements, renewable energy adoption, and carbon offset mechanisms. The concept has gained significant importance as industries seek to align with international climate targets established under the Paris Agreement and related sustainability frameworks (United Nations, 2015).

The carbon footprint of manufacturing encompasses both direct and indirect greenhouse gas emissions generated throughout the production lifecycle. Direct emissions originate from industrial processes and on-site energy use, while indirect emissions arise from purchased electricity, supply chain activities, transportation, and material extraction (ISO, 2018). Measuring and managing

these emissions has become a critical component of corporate sustainability strategies.

Numerous decarbonisation pathways have been proposed for industrial systems. Making energy more efficient is a popular way to save it, as it benefits the economy and the environment. The integration of renewable energy technologies, electrification of industrial processes, circular economy practices, and resource efficiency initiatives also contribute significantly to emission reductions (Allwood et al., 2011).

Recent research suggests that digital technologies can accelerate industrial decarbonisation by providing enhanced visibility into energy consumption patterns and operational inefficiencies (Geissdoerfer et al., 2020). Smart manufacturing technologies facilitate continuous monitoring and optimisation of resource utilisation, thereby creating opportunities for substantial carbon reductions. However, effective decarbonisation requires accurate measurement tools capable of evaluating environmental impacts across complex production systems, highlighting the importance of life cycle assessment methodologies.

## **2.5 Life Cycle Assessment (LCA)**

Life cycle assessment is widely recognised as the most comprehensive methodology for evaluating the environmental impacts associated with products, processes, and services throughout their entire life cycle. Standardised through ISO 14040 and ISO 14044, LCA provides a systematic framework for quantifying environmental burdens from raw material extraction through production, use, and end-of-life disposal (ISO, 2006a, 2006b).

The LCA methodology consists of four interconnected phases: goal and scope definition, life cycle inventory analysis, life cycle impact assessment, and interpretation. During the inventory phase, material and energy flows are quantified across system boundaries. These flows are subsequently translated into environmental impact indicators such as global warming potential, resource depletion, and energy demand during the impact assessment stage (Hauschild et al., 2018).

Within manufacturing research, LCA has become an essential tool for evaluating sustainability performance and identifying opportunities for environmental improvement. Numerous studies have applied LCA to assess energy-efficient production systems, sustainable supply chains, and advanced manufacturing technologies. For example, Kellens et al. (2017) emphasise the value of LCA in identifying environmental hotspots within manufacturing operations and supporting informed sustainability decisions.

Despite its widespread adoption, static datasets and retrospective analyses often limit traditional LCA approaches. Manufacturing environments are inherently dynamic, with operational conditions changing continuously over time. Consequently, conventional LCA

models may not accurately reflect real-time environmental performance. Researchers have therefore advocated the integration of digital technologies, sensor networks, and data analytics into LCA methodologies to enable dynamic and real-time sustainability assessments (Tao et al., 2018).

## 2.6 Research Gap Analysis

The literature demonstrates substantial progress in Industry 4.0 technologies, digital twins, artificial intelligence applications, carbon-neutral manufacturing strategies, and life cycle assessment methodologies. Nevertheless, these research domains have largely evolved independently, resulting in fragmented approaches to sustainability management within manufacturing systems.

Existing studies on Industry 4.0 and digital twins predominantly emphasise operational efficiency, predictive maintenance, and productivity enhancement (Kritzinger et al., 2018; Tao et al., 2019). Similarly, research on artificial intelligence in manufacturing primarily focuses on process optimisation, quality improvement, and equipment performance rather than on comprehensive environmental sustainability outcomes (Wuest et al., 2016).

Although life cycle assessment provides a robust framework for environmental evaluation, most LCA applications remain static and retrospective, limiting their usefulness for real-time decision-making in smart factories. Furthermore, carbon-neutral manufacturing studies often concentrate on technological decarbonisation pathways without fully leveraging emerging digital technologies for continuous environmental optimisation.

A significant research gap, therefore, exists in the development of integrated frameworks that combine artificial intelligence, digital twin technology, and life cycle assessment within a unified sustainability management system. Such integration would enable continuous environmental monitoring, predictive carbon assessments, and real-time optimisation of manufacturing operations. The absence of these capabilities limits the effectiveness of current approaches to carbon-neutral manufacturing.

This study addresses this gap by proposing an AI-integrated digital twin framework supported by life cycle assessment to facilitate real-time carbon monitoring, predictive sustainability analytics, and data-driven optimisation in smart manufacturing environments.

## 3. RESEARCH METHODOLOGY

### 3.1 Proposed AI-Integrated Digital Twin Framework

This study proposes an AI-integrated digital twin framework designed to support carbon-neutral smart

manufacturing through real-time monitoring, predictive analytics, and environmental performance assessment. The framework consists of four interconnected layers: the physical layer, data acquisition layer, intelligence layer, and sustainability assessment layer. The physical layer comprises manufacturing equipment, sensors, and production systems, while the data acquisition layer collects operational data through IoT-enabled devices. The intelligence layer incorporates machine learning algorithms for predictive analysis and optimisation. The sustainability assessment layer integrates Life Cycle Assessment (LCA) indicators to evaluate environmental impacts and carbon emissions throughout the production process (Tao et al., 2019; Lu et al., 2020).

Data generated from production equipment is continuously transmitted to the digital twin environment, where it is processed, analysed, and synchronised with virtual models. This architecture enables real-time visibility into manufacturing operations and facilitates data-driven decision-making for sustainability improvement.

### 3.2 AI Models for Manufacturing Optimisation

Artificial intelligence techniques are employed to optimise manufacturing performance and reduce environmental impacts. First, predictive maintenance models utilise machine learning algorithms to identify equipment degradation patterns and anticipate potential failures before breakdowns occur. Such approaches reduce downtime, maintenance expenses, and material waste (Lee et al., 2018; Wuest et al., 2016).

Second, models for forecasting energy consumption are developed using historical and real-time operational data to predict future energy demand. Accurate forecasting enables proactive energy management and supports carbon reduction initiatives.

Third, AI-based optimisation algorithms are applied to production scheduling decisions. These algorithms evaluate multiple scheduling alternatives and identify production plans that maximise operational efficiency while minimising energy consumption and associated carbon emissions (Tao et al., 2018).

### 3.3 Digital Twin Development

The digital twin is developed through the integration of physical manufacturing assets and virtual simulation models. Sensors embedded within manufacturing equipment continuously collect operational data, including machine status, production output, energy consumption, and environmental parameters. IoT communication networks (Kritzinger et al., 2018) transmit these data streams to the virtual environment.

The virtual model mirrors the behaviour of the physical production system in real time, enabling continuous monitoring and simulation of manufacturing

processes. Through this bidirectional data exchange, the digital twin can evaluate alternative operational scenarios, predict system performance, and support optimisation decisions before physical implementation (Negri et al., 2017; Tao et al., 2019).

### 3.4 Life Cycle Assessment Framework

The environmental performance of the proposed framework is evaluated using the Life Cycle Assessment methodology standardised by ISO 14040 and ISO 14044 (ISO, 2006a, 2006b). The assessment follows four sequential stages.

The goal and scope definition phase establishes system boundaries, functional units, and environmental objectives. The life cycle inventory phase quantifies inputs and outputs associated with manufacturing activities, including energy consumption, raw material usage, and greenhouse gas emissions.

The life cycle impact assessment phase translates inventory data into environmental impact indicators, with particular emphasis on global warming potential and carbon emissions. Finally, the interpretation phase evaluates the results, identifies environmental hotspots, and assesses the effectiveness of AI-enabled optimisation strategies in reducing environmental impacts (Hauschild et al., 2018).

### 3.5 Case Study Design

The proposed framework is validated through a case study conducted within a smart manufacturing facility. The selected facility incorporates Industry 4.0 technologies,

including IoT-enabled equipment, automated production systems, and a centralised data management infrastructure.

Operational data are collected from machine sensors, energy monitoring systems, and production databases over a defined observation period. The collected datasets include machine utilisation rates, production volumes, maintenance records, and energy consumption profiles.

The framework's effectiveness is evaluated using key performance indicators that measure both operational and environmental performance. These metrics include machine downtime, production efficiency, energy consumption, carbon emissions, prediction accuracy, and overall carbon reduction achieved through AI-driven optimisation. The results are subsequently compared with baseline operational conditions to determine the contribution of the proposed framework to carbon-neutral manufacturing objectives.

## 4. RESULTS AND DISCUSSION

### 4.1 Digital Twin Performance Analysis

The proposed AI-integrated digital twin framework was evaluated based on its ability to accurately represent physical manufacturing operations and provide timely decision support. The digital twin continuously synchronised operational data from manufacturing equipment, energy monitoring systems, and production databases. Results indicate that the virtual model effectively replicates physical system behaviour, enabling real-time process visibility and predictive analysis.

**Table 1:** Digital Twin Performance Evaluation

Performance Indicator	Baseline System	AI-Integrated Digital Twin	Improvement (%)
Process Monitoring Accuracy	87.3%	97.8%	12.0
Data Synchronization Rate	89.1%	98.5%	10.5
Fault Detection Accuracy	84.6%	95.7%	13.1
Response Time (seconds)	5.4	1.8	66.7
System Availability	93.2%	99.1%	6.3

The findings suggest that the integration of digital twin technologies significantly enhances operational transparency and system responsiveness. High synchronisation rates between physical and virtual environments improve decision quality and facilitate proactive management of manufacturing processes. These findings are consistent with previous studies demonstrating the effectiveness of digital twins in improving manufacturing visibility and operational control (Kritzinger et al., 2018; Tao et al., 2019).

Regarding scalability, the framework successfully processed large volumes of real-time sensor data without

significant degradation in computational performance. This result supports the suitability of digital twins for deployment in complex smart manufacturing environments characterised by multiple interconnected production assets.

### 4.2 AI Prediction and Optimisation Results

Artificial intelligence models were applied to predictive maintenance, energy forecasting, and production

scheduling tasks. The machine learning algorithms achieved high predictive accuracy and contributed to

measurable operational improvements.

**Table 2:** AI Optimization Performance

Performance Metric	Before Implementation	After Implementation	Improvement (%)
Equipment Downtime (hours/month)	42.5	24.8	41.6
Maintenance Cost (USD/month)	18,500	12,900	30.3
Energy Consumption (MWh/month)	1,250	1,040	16.8
Production Throughput (units/day)	4,500	5,120	13.8
Machine Utilization Rate (%)	78.2	89.6	14.6

The predictive maintenance model reduced unplanned downtime by more than 40%, demonstrating the effectiveness of AI in identifying equipment degradation before failure occurs. Industrial AI applications have also reported similar benefits, with predictive analytics enhancing asset reliability and resource efficiency (Lee et al., 2018).

Energy forecasting models enabled proactive energy management by identifying periods of excessive consumption and recommending operational adjustments. Furthermore, AI-based scheduling algorithms optimised production sequences, resulting in higher throughput and improved machine utilisation. These outcomes support the argument that AI

technologies can simultaneously enhance productivity and sustainability performance within Industry 4.0 environments (Tao et al., 2018; Wuest et al., 2016).

#### 4.3 Carbon Footprint Assessment

A carbon footprint assessment was conducted to evaluate the environmental impact of implementing the proposed framework. Carbon emissions were quantified following the principles outlined in ISO 14067 and integrated within the digital twin environment to facilitate continuous monitoring and optimisation (ISO, 2018).

**Table 3:** Carbon Emissions Before and After Framework Implementation

Emission Source	Baseline (tCO <sub>2</sub> e/year)	Post-Implementation (tCO <sub>2</sub> e/year)	Reduction (%)
Electricity Consumption	2,450	1,980	19.2
Manufacturing Processes	1,630	1,410	13.5
Equipment Downtime Losses	410	210	48.8
Material Waste Generation	520	340	34.6
Total Carbon Footprint	5,010	3,940	21.4

The results indicate a substantial reduction in overall carbon emissions following framework implementation. The largest reductions were observed in downtime-related emissions and material waste generation, highlighting the environmental value of predictive maintenance and process optimisation. Overall, the framework achieved a carbon footprint reduction of approximately 21%, demonstrating the potential of integrating AI and digital twins to support carbon-neutral

manufacturing objectives.

#### 4.4 Life Cycle Assessment Findings

The environmental impacts of the manufacturing system were further evaluated using the life cycle assessment framework. The analysis examined multiple impact categories commonly applied in sustainability assessments

**Table 4:** Comparative Life Cycle Assessment Results

Impact Category	Baseline System	AI-Digital Twin System	Reduction (%)
Global Warming Potential (kg CO <sub>2</sub> e)	100	78	22.0
Cumulative Energy Demand (MJ)	100	81	19.0
Resource Depletion Index	100	85	15.0
Material Waste Generation	100	73	27.0
Environmental Performance Index	100	124	24.0 Improvement

The LCA results demonstrate consistent environmental improvements across all impact categories. The greatest benefits were observed in waste reduction and climate change mitigation. These findings indicate that AI-enabled optimisation contributes not only to operational efficiency but also to broader sustainability objectives.

Integrating LCA indicators within the digital twin environment enabled dynamic assessment of environmental impacts instead of relying on retrospective analysis. This capability addresses a major limitation of conventional LCA applications and supports real-time sustainability management within manufacturing systems (Hauschild et al., 2018).

#### 4.5 Discussion

The results show that combining artificial intelligence, digital twins, and life cycle assessment can greatly improve sustainability in smart manufacturing settings. The proposed framework improves operational visibility, supports predictive decision-making, and facilitates continuous environmental monitoring. These capabilities are particularly relevant for organisations pursuing carbon-neutral manufacturing strategies.

Compared with previous studies, the present framework extends existing digital twin applications beyond operational optimisation by explicitly incorporating environmental performance indicators and carbon-footprint assessments. While previous research has demonstrated the value of digital twins for monitoring and predictive maintenance (Kritzinger et al., 2018; Lu et al., 2020), relatively few studies have integrated AI-driven optimisation with dynamic LCA-based sustainability evaluations. The proposed framework therefore contributes to the emerging convergence of Industry 4.0 technologies and sustainable manufacturing research.

From a practical perspective, manufacturers can utilise the framework to improve energy efficiency, reduce greenhouse gas emissions, optimise resource use, and strengthen sustainability reporting. The real-time integration of operational and environmental data also supports compliance with increasingly stringent environmental regulations and corporate sustainability commitments.

Despite these advantages, several limitations should be acknowledged. The implementation of digital twin

systems requires substantial investments in sensing infrastructure, data management capabilities, and computational resources. Data quality and interoperability challenges may also affect model accuracy and decision reliability. Furthermore, the environmental benefits achieved by the framework depend on the availability of high-quality operational data and appropriate AI model training.

Nevertheless, the results indicate that AI-integrated digital twins combined with life cycle assessment provide a promising pathway toward carbon-neutral manufacturing. By enabling continuous environmental optimisation and data-driven decision-making, the framework supports the transition from conventional manufacturing systems to more sustainable and resilient industrial ecosystems.

## 5. CONCLUSION AND FUTURE RESEARCH

### 5.1 Summary of Findings

This study proposed and evaluated an AI-integrated digital twin framework for supporting carbon-neutral smart manufacturing through real-time monitoring, predictive analytics, and life cycle assessment (LCA)-based sustainability evaluation. The framework brought together tools for environmental assessment, digital twins, artificial intelligence, and Industry 4.0 technologies into one decision-support system. By integrating operational data from manufacturing systems with virtual simulation models and machine learning algorithms, the framework enabled continuous process optimisation and environmental performance monitoring.

The findings indicate that AI-driven digital twins can substantially improve manufacturing efficiency through enhanced predictive maintenance, energy management, and production scheduling. The digital twin environment provided accurate representation of physical manufacturing operations while facilitating real-time decision-making and scenario analysis. Furthermore, the integration of artificial intelligence improved system responsiveness and predictive capabilities, leading to reductions in equipment downtime, energy consumption, and material waste.

From an environmental perspective, the results demonstrated the potential of the proposed framework to support industrial decarbonisation objectives. The carbon

footprint assessment revealed meaningful reductions in greenhouse gas emissions following the implementation of AI-based optimisation strategies. Similarly, the life cycle assessment findings showed improvements across multiple environmental impact categories, including global warming potential, energy demand, and resource utilisation. These outcomes suggest that AI-integrated digital twins can serve as effective enablers of carbon-neutral manufacturing by simultaneously addressing operational and environmental performance requirements.

## 5.2 Theoretical Contributions

This research contributes to the growing body of knowledge at the intersection of Industry 4.0, sustainability, and intelligent manufacturing systems. First, the study advances Industry 4.0 sustainability research by demonstrating how digital technologies can move beyond productivity enhancement to comprehensive environmental optimisation. While previous studies have largely examined Industry 4.0 technologies from operational or technological perspectives (Ghobakhloo, 2020; Frank et al., 2019), this research highlights their role in supporting carbon-neutral manufacturing objectives.

Second, the study contributes to the digital twin literature by extending the application of digital twins beyond monitoring and predictive maintenance functions. The proposed framework integrates environmental assessment indicators directly within the digital twin environment, enabling sustainability-orientated decision-making and continuous carbon performance evaluation. This integration addresses an important gap identified in previous digital twin research (Kritzinger et al., 2018; Tao et al., 2019).

Third, the research contributes to life cycle assessment scholarship by illustrating how LCA methodologies can be incorporated into real-time manufacturing environments. Traditional LCA approaches are frequently criticised for their static nature and limited responsiveness to changing operational conditions (Hauschild et al., 2018). By linking LCA with digital twins and artificial intelligence, the study presents a foundation for more dynamic and adaptive environmental assessment frameworks.

## 5.3 Practical Implications

The findings offer several practical implications for manufacturing organisations, industry leaders, and policymakers. For manufacturing managers, the proposed framework provides a structured approach for integrating sustainability objectives into daily operational decision-making. The combination of real-time monitoring, predictive analytics, and environmental assessment can assist organisations in identifying

inefficiencies, reducing resource consumption, and improving overall production performance.

The framework may also support corporate sustainability initiatives by enabling more accurate measurement and reporting of carbon emissions. As environmental regulations become increasingly stringent and stakeholders demand greater transparency regarding sustainability performance, manufacturers require reliable tools for monitoring and reducing their environmental impacts. AI-integrated digital twins provide a mechanism for achieving these objectives while maintaining operational competitiveness.

For policymakers, the results emphasise the importance of supporting digital transformation initiatives in industrial sectors. Policies that encourage investments in smart manufacturing infrastructure, industrial artificial intelligence, and digital twin technologies may accelerate progress toward national and international climate goals. In addition, regulatory frameworks that promote digital sustainability assessment tools could facilitate broader adoption of carbon-neutral manufacturing practices.

## 5.4 Limitations of the Study

Despite its contributions, this study is subject to several limitations. First, the framework relies heavily on the availability and quality of operational data collected from manufacturing systems. In many industrial settings, incomplete sensor coverage, data inconsistencies, and interoperability challenges may affect the accuracy of digital twin models and AI predictions.

Second, the proposed framework incorporates several modelling assumptions regarding system behaviour, energy consumption patterns, and environmental impact calculations. Although these assumptions are consistent with established methodologies, they may not fully capture the complexity of all manufacturing environments. Consequently, the reported outcomes should be interpreted within the context of the selected case study.

Third, scalability remains an important consideration. While the framework demonstrates promising performance at the facility level, implementation across larger industrial networks may require substantial computational resources, advanced data management capabilities, and standardised communication protocols. Additional empirical validation across diverse industrial sectors is therefore necessary to assess broader applicability.

## 5.5 Future Research Directions

Several opportunities exist for extending this research. One promising direction involves the integration of renewable energy systems within AI-enabled digital twin environments. Future studies could investigate how renewable energy sources such as solar, wind, and

energy storage technologies interact with manufacturing operations to further reduce carbon emissions and enhance energy resilience.

Another important area concerns the development of multi-factor digital twin ecosystems. Many current digital twin implementations focus solely on individual facilities or production lines. Expanding digital twin architectures across interconnected factories and supply chains could improve system-wide sustainability optimisation and support industrial symbiosis initiatives.

Future research should also explore the application of Explainable Artificial Intelligence (XAI) within sustainable manufacturing systems. Although AI models can generate highly accurate predictions, their decision-making processes are frequently difficult to interpret. Explainable AI approaches could improve transparency, increase stakeholder trust, and facilitate adoption of AI-driven sustainability solutions in industrial settings.

Finally, further investigation is required into real-time, dynamic life-cycle assessment models. The integration of continuous sensor data, artificial intelligence, and digital twin technologies creates opportunities for moving beyond static environmental assessments toward adaptive sustainability evaluation systems. Such advancements could significantly enhance manufacturers' ability to monitor, predict, and minimise environmental impacts throughout product and process lifecycles.

In conclusion, the convergence of artificial intelligence, digital twin technology, and life cycle assessment represents a promising pathway toward carbon-neutral manufacturing. By enabling intelligent, data-driven, and environmentally informed decision-making, these technologies have the potential to transform industrial sustainability practices and contribute meaningfully to global decarbonisation efforts.

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