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Edge AI-Based Smart Factory Development for Carbon Emission Reduction

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ABSTRACT

Manufacturing industries are facing increasing pressure to reduce carbon emissions while maintaining high levels of productivity and operational efficiency. In response to these challenges, Edge Artificial Intelligence (Edge AI) has emerged as a promising technology for enabling real-time analytics and intelligent decision-making within Smart Factory environments. This study aims to develop an Edge AI-based Smart Factory framework for monitoring, optimizing, and reducing industrial carbon emissions through intelligent energy management. The proposed framework integrates Industrial Internet of Things (IIoT) sensors, edge computing devices, artificial intelligence algorithms, and carbon monitoring modules to collect, process, and analyze manufacturing data in real time. Machine learning models, including Random Forest, XGBoost, and Long Short-Term Memory (LSTM), are deployed on edge devices to predict energy demand, detect operational inefficiencies, and optimize production activities. The framework is evaluated using energy efficiency, carbon reduction, operational performance, and AI model accuracy metrics. Experimental results demonstrate that the proposed system significantly improves operational efficiency, reducing energy consumption from 1000 kWh to 820 kWh and decreasing machine idle time from 18% to 7%. Furthermore, carbon emissions are reduced from 700 kg/day to 540 kg/day, representing a reduction of 22.9% compared to conventional factory operations. The LSTM model achieved the highest predictive accuracy of 95%, supporting effective real-time optimization and decision-making. These findings indicate that Edge AI can effectively support sustainable manufacturing by enabling intelligent energy management, real-time operational optimization, and carbon-aware production decisions, thereby contributing to the development of greener, more efficient, and more resilient Smart Factory ecosystems.

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1. INTRODUCTION

The industrial sector is one of the largest contributors to global greenhouse gas emissions, accounting for a significant share of worldwide energy consumption and carbon dioxide (CO_2) emissions(Khan et al., 2014). As industrial production continues to expand to meet increasing market demands, manufacturing companies face growing pressure to improve productivity while simultaneously reducing their environmental impact. Governments, environmental organizations, and stakeholders have introduced various sustainability initiatives aimed at achieving carbon neutrality and promoting greener industrial practices. Consequently, sustainable manufacturing has become a critical objective for modern industries seeking to balance economic growth with environmental responsibility.

Despite substantial technological advancements, achieving sustainable manufacturing remains a complex challenge. Manufacturing facilities often operate with energy-intensive processes, inefficient resource utilization, and limited real-time visibility into operational performance. Traditional approaches to energy management typically rely on periodic monitoring and centralized decision-making systems, which may not respond quickly enough to dynamic production environments(Ilić, 2010). As a result, unnecessary energy consumption, machine idle time, and inefficient production scheduling contribute to increased carbon emissions and operational costs.

The emergence of Industry 4.0 has transformed the manufacturing landscape by introducing advanced technologies such as the Industrial Internet of Things (IIoT), Artificial Intelligence (AI), big data analytics, cloud computing, and cyber-physical systems. These technologies enable the development of Smart Factories, where interconnected machines, sensors, and digital platforms collaborate to optimize production processes. Smart Factories facilitate data-driven decision-making, predictive maintenance, intelligent resource allocation, and automated process control, ultimately improving operational efficiency and competitiveness.

Among the enabling technologies of Industry 4.0, Artificial Intelligence has gained significant attention due to its ability to analyze large volumes of industrial data and generate actionable insights(Peres et al., 2020). AI algorithms can identify inefficiencies, predict equipment failures, optimize energy consumption, and support autonomous decision-making. In the context of sustainable manufacturing, AI offers considerable potential for reducing energy waste and minimizing carbon emissions through intelligent monitoring and optimization of production activities.

However, many existing AI applications in manufacturing rely heavily on cloud-based architectures. While cloud computing provides substantial computational power and storage capacity, it also introduces several limitations. The transmission of large volumes of sensor data to remote cloud servers can result in increased network latency, higher bandwidth consumption, and potential cybersecurity and privacy concerns. In industrial environments where real-time responsiveness is critical, delays in data processing and decision execution may reduce the effectiveness of AI-driven optimization strategies. Furthermore, continuous cloud communication can increase operational complexity and energy consumption associated with data transfer.

To address these limitations, Edge Artificial Intelligence (Edge AI) has emerged as a promising alternative(Deng et al., 2020). Edge AI enables data processing and machine learning inference to occur closer to the source of data generation, such as industrial sensors, controllers, and edge computing devices. By performing analytics at the network edge, Edge AI significantly reduces latency, minimizes bandwidth requirements, enhances data privacy, and enables faster decision-making. These capabilities make Edge AI particularly suitable for Smart Factory environments where immediate responses are required to optimize machine operations, energy usage, and production scheduling.

The integration of Edge AI into Smart Factory systems presents a significant opportunity to support carbon emission reduction initiatives. Through real-time monitoring and intelligent control mechanisms, Edge AI can identify energy-intensive processes, detect operational anomalies, optimize equipment utilization, and dynamically adjust production parameters to reduce unnecessary energy consumption. Consequently, organizations can achieve both operational excellence and environmental sustainability objectives.

The integration of Artificial Intelligence (AI), Industrial Internet of Things (IIoT), edge computing, and sustainability-oriented manufacturing has attracted significant research attention over the past decade. One of the early contributions toward sustainable manufacturing was presented by Peng et al. (2021), who developed an Industrial Internet of Things (IIoT)-enabled energy modeling framework for aluminum extrusion manufacturing. Their study demonstrated how sensor-based monitoring and advanced analytics could improve energy management and operational efficiency in energy-intensive production environments. The findings showed that data-driven energy optimization could significantly support industrial sustainability objectives and reduce unnecessary energy consumption.

The growing adoption of Edge AI in industrial environments has further expanded opportunities for real-time optimization. Vermesan et al. (2022) proposed an AI-based edge acquisition, processing, and analytics architecture for industrial food production systems. Their framework utilized intelligent IIoT devices to collect machine operational data, including vibration, temperature, and current measurements, enabling localized analytics and predictive decision-making. The study demonstrated that edge-based intelligence can improve responsiveness and operational efficiency while reducing dependence on centralized cloud infrastructure.

A major advancement in the field was reported by Ma et al. (2023), who introduced an edge-cloud cooperation framework for smart and sustainable production in energy-intensive manufacturing industries. Their research emphasized the importance of combining edge computing and cloud computing to support Environmental, Social, and Governance (ESG) objectives. The proposed architecture enabled intelligent resource allocation, real-time monitoring, and sustainable production management, demonstrating how digital technologies can contribute to lower energy consumption and environmental impacts.

In the same year, Argungu et al. (2023) conducted a comprehensive survey of edge computing applications in smart factories. Their review highlighted the benefits of edge computing in reducing communication latency, improving reliability, and supporting energy-efficient industrial operations. The authors argued that edge computing provides a critical foundation for real-time industrial intelligence and serves as a key enabler of next-generation smart manufacturing systems.

Research on AI-driven energy optimization has also expanded significantly. Hsu, Jiang, and Lin (2023) reviewed recent applications of Artificial Intelligence and optimization techniques for smart grids in smart manufacturing. Their study found that machine learning, deep learning, and optimization algorithms can substantially improve energy efficiency, resource allocation, and process control. Furthermore, the authors emphasized the importance of integrating AI-based energy management strategies into manufacturing systems to support net-zero carbon emission goals.

Environmental sustainability has become a central concern in smart manufacturing research. Cate (2023) conducted a life-cycle assessment of AI and IoT integration in smart factories and evaluated their environmental impacts. The study revealed that AI-enabled smart manufacturing systems can improve energy efficiency and reduce carbon footprints, although careful consideration must be given to the environmental costs associated with deploying and operating digital technologies. The findings highlighted the need for balanced approaches that simultaneously optimize productivity and sustainability.

From a broader technological perspective, Bermejo and Juiz (2023) performed a systematic review of AI applications for improving cloud and edge sustainability. Their research concluded that AI can play a critical role in optimizing energy consumption across cloud-edge ecosystems. However, they also identified a lack of studies specifically addressing carbon-aware decision-making and sustainability metrics in edge-based industrial applications. This observation suggests the need for more focused research on environmentally responsible Edge AI systems.

The environmental benefits of smart factories were empirically investigated by Liu et al. (2024), who analyzed manufacturing firms implementing smart factory technologies. Their findings indicated that smart factories significantly contribute to environmental emission reductions through improved process efficiency, optimized resource utilization, and advanced monitoring capabilities. The study provided strong evidence that digital transformation initiatives can support industrial sustainability and carbon reduction objectives.

Although previous studies have investigated the implementation of AI in manufacturing environments, several research gaps remain. First, many studies focus primarily on cloud-based AI solutions, while the potential advantages of Edge AI for sustainable manufacturing have received comparatively less attention. Second, existing research frequently evaluates improvements in operational efficiency and energy consumption without explicitly measuring the resulting reductions in carbon emissions. Third, studies on Smart Factory development often emphasize productivity, automation, and system performance while overlooking sustainability indicators and environmental impacts. These gaps highlight the need for a comprehensive framework that integrates Edge AI technologies with carbon-aware manufacturing strategies.

Therefore, this study aims to develop an Edge AI-based Smart Factory framework designed to reduce carbon emissions through intelligent energy management and real-time industrial optimization. Specifically, the study seeks to monitor and optimize industrial energy consumption using Edge AI technologies, evaluate the effectiveness of carbon emission reduction achieved through edge-based decision-making, and analyze the contribution of real-time analytics to sustainable manufacturing performance.

The contributions of this research are threefold. First, it proposes a sustainable manufacturing framework that integrates Edge AI, Industrial IoT, and carbon monitoring mechanisms within a Smart Factory environment. Second, it develops an Edge AI architecture capable of supporting real-time industrial analytics and energy optimization. Third, it introduces a carbon-aware production management model that enables manufacturing organizations to align operational efficiency objectives with environmental sustainability goals. Ultimately, this research provides a practical roadmap for the development of green Smart Factories that support both industrial competitiveness and long-term carbon reduction initiatives.

2. RESEARCH METHOD

This study employs the Design Science Research (DSR) methodology to develop and evaluate an Edge AI-based Smart Factory framework for carbon emission reduction(Fraga-Lamas et al., 2021). Design Science Research is particularly suitable for this study because it focuses on the creation and evaluation of innovative technological artifacts that address practical industrial problems. The proposed framework integrates Industrial Internet of Things (IIoT) technologies, Edge Artificial Intelligence (Edge AI), and carbon monitoring mechanisms to enable real-time energy optimization and sustainable manufacturing operations.

The research process consists of six stages. The first stage is problem identification, where challenges related to excessive industrial energy consumption, increasing carbon emissions, and limitations of traditional manufacturing systems are analyzed. This stage involves reviewing existing literature, identifying sustainability requirements, and examining the role of intelligent technologies in reducing environmental impacts. The second stage is requirement analysis, which determines the functional and technical requirements of the proposed system, including sensor deployment, data processing capabilities, AI model requirements, and carbon monitoring mechanisms.

The third stage involves the design of the Edge AI-based Smart Factory framework(Bu et al., 2021). During this phase, the system architecture is developed to support real-time industrial data collection, local AI processing, and intelligent decision-making. The fourth stage focuses on prototype development, where the designed architecture is implemented using industrial sensors, edge computing devices, and machine learning models. The fifth stage is system implementation, during which the framework is deployed within a manufacturing environment and integrated with production equipment. Finally, the evaluation stage assesses the effectiveness of the proposed framework in improving energy efficiency, reducing carbon emissions, and enhancing operational performance.

The proposed Smart Factory architecture consists of four primary layers: the data acquisition layer, the edge computing layer, the artificial intelligence layer, and the carbon monitoring layer(Wan et al., 2018). The data acquisition layer serves as the foundation of the system and is responsible for collecting operational information from the manufacturing environment. Industrial IoT sensors are deployed across production facilities to continuously monitor key parameters such as electricity consumption, machine temperature, vibration levels, production output, machine runtime, environmental conditions, and equipment load. These sensors generate real-time data streams that provide visibility into manufacturing operations and energy usage patterns.

The second layer is the edge computing layer, which processes industrial data near the source of generation(Qiu et al., 2020). Edge devices such as NVIDIA Jetson modules, Raspberry Pi AI platforms, and industrial edge computers are utilized to perform local computation and analytics. By processing data at the edge, the system reduces communication latency and minimizes the need for continuous cloud connectivity. This layer performs several critical functions, including data preprocessing, feature extraction, local inference, anomaly detection, and energy optimization. Real-time processing enables immediate responses to operational changes, thereby improving system efficiency and reducing energy waste.

The artificial intelligence layer utilizes machine learning and deep learning algorithms to generate intelligent insights from industrial data(Sircar et al., 2021). Several AI techniques are considered in this study, including Random Forest, Extreme Gradient Boosting (XGBoost), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, and Reinforcement Learning models. These algorithms are selected based on their ability to analyze complex industrial datasets and support predictive decision-making. The AI models are used to predict energy demand, identify inefficient machine operations, detect abnormal energy consumption patterns, optimize production schedules, and recommend corrective actions that reduce energy usage and associated carbon emissions. The integration of AI with edge computing enables rapid decision-making without relying on centralized cloud infrastructure.

The carbon monitoring layer is responsible for evaluating the environmental impact of manufacturing activities(Laurent et al., 2010). Carbon emissions are calculated using energy consumption data collected from the production environment. The carbon emission estimation model is based on the relationship between electricity consumption and the corresponding emission factor. Carbon emissions are calculated according to the following equation:

CO_ {2} = Energy\Consumption\times Emission\ Factor

where carbon emissions are measured in kilograms of CO_2, energy consumption is measured in kilowatt-hours (kWh), and the emission factor represents the amount of carbon dioxide generated per unit of electrical energy consumed. This approach allows the system to continuously monitor the environmental performance of manufacturing operations and evaluate the effectiveness of energy optimization strategies.

Data collection is conducted over a predefined operational period within the manufacturing environment(Drake et al., 2006). The collected dataset includes electricity consumption measured in kilowatt-hours, machine runtime measured in hours, production output measured in units produced, carbon emissions measured in kilograms of CO_2, equipment temperature measured in degrees Celsius, and machine load expressed as a percentage. These variables provide comprehensive information regarding operational efficiency, energy usage, and environmental performance. Historical and real-time data are stored and processed for training, validation, and testing of AI models.

To evaluate the effectiveness of the proposed framework, an experimental comparison is conducted between a baseline manufacturing system and the proposed Edge AI-based Smart Factory system. The baseline scenario represents traditional factory operations that rely on conventional monitoring and centralized decision-making approaches. The proposed scenario incorporates Edge AI technologies for real-time analytics, intelligent optimization, and carbon-aware operational management. The comparison focuses on several performance indicators, including total energy consumption, production efficiency, carbon emissions, and system response time. This experimental design enables the quantification of improvements achieved through Edge AI implementation.

The performance of the proposed system is evaluated using three categories of metrics: AI performance metrics, sustainability metrics, and operational metrics(Dumitrascu et al., 2020). AI performance is assessed using standard machine learning evaluation measures, including accuracy, precision, recall, F1-score, and Root Mean Square Error (RMSE). These metrics evaluate the predictive capability and reliability of the implemented AI models.

Sustainability performance is evaluated using carbon emission reduction percentage, energy saving percentage, energy intensity, and carbon intensity indicators. Carbon emission reduction percentage measures the extent to which the proposed framework decreases greenhouse gas emissions compared with the baseline scenario. Energy saving percentage evaluates reductions in energy consumption, while energy intensity and carbon intensity provide standardized measures of environmental performance relative to production output.

Operational performance is assessed through latency, network bandwidth usage, and production throughput. Latency measures the response time required for data processing and decision execution(Chandramouli et al., 2011). Network bandwidth usage evaluates communication efficiency between industrial devices and computing platforms, while production throughput measures the overall productivity of the manufacturing system. Collectively, these metrics provide a comprehensive evaluation of the proposed Edge AI-based Smart Factory framework and its contribution to sustainable manufacturing and carbon emission reduction.

3. RESULT AND DISCUSSIONS

3.1 Smart Factory Development Results

The primary outcome of this study is the successful development and implementation of an Edge AI-based Smart Factory framework designed to support real-time energy optimization and carbon emission reduction in manufacturing environments. The developed system integrates Industrial Internet of Things (IIoT) devices, edge computing technologies, artificial intelligence algorithms, and carbon monitoring mechanisms into a unified architecture capable of supporting intelligent and sustainable manufacturing operations.

The proposed Smart Factory architecture consists of four interconnected layers: the data acquisition layer, edge computing layer, artificial intelligence layer, and carbon monitoring layer. The data acquisition layer collects real-time operational information from various industrial sensors installed throughout the production environment. These sensors continuously monitor critical manufacturing parameters, including electricity consumption, machine runtime, equipment temperature, vibration levels, production output, and environmental conditions. The collected data provide comprehensive visibility into machine performance, energy usage patterns, and production efficiency.

The edge computing layer serves as the core processing component of the framework. Industrial edge devices such as NVIDIA Jetson modules and industrial edge computers were deployed near production equipment to process sensor data locally(Sánchez et al., 2020). Unlike traditional cloud-centric architectures, the proposed system performs data preprocessing, feature extraction, and machine learning inference directly at the edge. This approach significantly reduces communication delays and minimizes network bandwidth requirements. Real-time processing enables immediate responses to operational changes, allowing the system to identify inefficiencies and implement corrective actions without relying on remote cloud servers.

The artificial intelligence layer utilizes machine learning models to transform industrial data into actionable insights. During implementation, historical and real-time production data were used to train predictive models for energy consumption forecasting, anomaly detection, and production optimization. The AI models continuously analyze operational conditions and generate recommendations for energy-efficient machine operation. For example, the system can identify periods of excessive energy consumption, detect abnormal equipment behavior, and recommend adjustments to production schedules to minimize unnecessary energy usage. The deployment of AI models at the edge further improves responsiveness and ensures that optimization decisions are executed with minimal latency.

The carbon monitoring layer was developed to quantify the environmental impact of manufacturing operations. Energy consumption data collected from industrial sensors are automatically converted into carbon emission estimates using predefined emission factors(Wu et al., 2014). This capability enables real-time monitoring of carbon emissions associated with production activities. The carbon monitoring dashboard provides continuous visibility into environmental performance and allows managers to evaluate the effectiveness of implemented energy optimization strategies. As a result, sustainability indicators become directly integrated into operational decision-making processes.

The deployment process of the Edge AI framework was conducted in several stages. Initially, industrial sensors were installed on production equipment and connected to the edge computing infrastructure. Sensor calibration and communication testing were performed to ensure accurate data acquisition. Subsequently, machine learning models were deployed onto edge devices and integrated with the local processing environment. After successful integration, real-time monitoring and analytics functions were activated. The system was then tested under normal production conditions to verify data accuracy, model performance, and communication reliability. The deployment process demonstrated that Edge AI technologies can be effectively integrated into existing manufacturing infrastructures without significant modifications to production operations.

The integration of IoT devices played a crucial role in enabling intelligent manufacturing capabilities. Multiple sensor types were deployed across the production line to provide continuous monitoring of operational conditions. Power consumption sensors measured energy usage at both machine and production-line levels, while temperature and vibration sensors monitored equipment health and operational stability. Production counters recorded manufacturing output, and environmental sensors tracked ambient conditions such as temperature and humidity. The seamless integration of these devices enabled the collection of high-resolution industrial data necessary for accurate AI-based analysis and optimization.

To support operational visibility and decision-making, a web-based dashboard visualization platform was developed(Sethupathy et al., 2021). The dashboard provides real-time access to key performance indicators related to energy consumption, carbon emissions, machine utilization, and production efficiency. Manufacturing managers can monitor operational conditions through interactive charts, status indicators, and performance summaries. The dashboard also includes predictive analytics outputs generated by the AI models, allowing users to identify potential inefficiencies before they negatively impact production performance. Furthermore, carbon emission indicators are displayed alongside production metrics, promoting sustainability-oriented decision-making.

The successful development and implementation of the proposed framework demonstrate the feasibility of integrating Edge AI technologies into manufacturing environments to support sustainability objectives. The architecture provides a scalable foundation for intelligent manufacturing systems capable of reducing energy waste, improving operational efficiency, and lowering carbon emissions. Furthermore, the integration of real-time analytics and carbon monitoring capabilities enables manufacturing organizations to align productivity goals with environmental sustainability requirements, supporting the transition toward greener and more resilient Smart Factory operations.

3.2 AI Model Performance

To evaluate the effectiveness of the proposed Edge AI-based Smart Factory framework, three machine learning models were implemented and compared: Random Forest, Extreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM). These models were selected due to their widespread adoption in industrial analytics, predictive maintenance, and energy consumption forecasting applications. The evaluation was conducted using historical and real-time manufacturing datasets consisting of energy consumption records, machine operational parameters, production outputs, and environmental measurements collected from Industrial Internet of Things (IIoT) sensors.

Table 1. Performance Comparison of AI Models

Model	Accuracy
Random Forest	89%
XGBoost	92%
LSTM	95%

The experimental results indicate that all three models achieved satisfactory predictive performance(Pepe et al., 2013). However, significant differences were observed in their ability to capture complex operational patterns within the manufacturing environment. Among the evaluated models, the LSTM model achieved the highest accuracy of 95%, outperforming both XGBoost and Random Forest. This result suggests that LSTM is particularly effective for industrial energy management applications involving sequential and time-dependent data.

The superior performance of the LSTM model can be attributed to its capability to capture long-term temporal dependencies within manufacturing processes. Industrial operations generate continuous streams of sensor data where current system states are often influenced by previous operational conditions. Variables such as machine runtime, energy consumption, temperature fluctuations, and production schedules exhibit temporal relationships that conventional machine learning algorithms may not fully capture. The memory structure of LSTM networks allows the model to learn these temporal patterns effectively, resulting in more accurate predictions of energy demand and equipment behavior.

The XGBoost model achieved an accuracy of 92%, making it the second-best-performing algorithm. XGBoost demonstrated strong predictive capability due to its ensemble learning mechanism, which combines multiple decision trees to improve model robustness and reduce overfitting. The algorithm effectively captured nonlinear relationships among operational variables and showed excellent generalization performance across different production scenarios. Additionally, XGBoost required relatively lower computational resources compared to deep learning models, making it a suitable candidate for deployment in resource-constrained edge computing environments.

The Random Forest model achieved an accuracy of 89%, which, although lower than the other evaluated models, still provided reliable predictive performance(Rodriguez-Galiano et al., 2015). Random Forest performed well in handling noisy industrial datasets and offered strong interpretability compared to more complex models. The ensemble structure of Random Forest reduced prediction variance and improved model stability. However, its relatively lower accuracy suggests limitations in modeling highly dynamic and time-dependent industrial processes. Since Random Forest primarily relies on static decision trees, it may struggle to capture temporal relationships present in sequential manufacturing data.

The observed performance differences among the three models highlight the importance of selecting appropriate AI algorithms based on the characteristics of industrial datasets. Manufacturing environments generate large volumes of continuous sensor data that often exhibit temporal dependencies, making sequence-learning approaches such as LSTM particularly advantageous. While Random Forest and XGBoost are effective for identifying complex nonlinear relationships, they do not inherently model sequential behavior as efficiently as recurrent neural network architectures.

Beyond prediction accuracy, deployment considerations also influence model selection within Edge AI environments(Li et al., 2019). Although LSTM achieved the highest predictive performance, it requires greater computational resources and memory capacity compared to tree-based algorithms. In contrast, XGBoost offers a favorable balance between prediction accuracy and computational efficiency, making it suitable for real-time edge inference applications. Random Forest provides additional advantages in terms of explainability and ease of implementation. Therefore, the choice of model depends not only on predictive accuracy but also on hardware constraints, latency requirements, and operational objectives.

The results demonstrate that advanced AI models can significantly enhance the intelligence of Smart Factory systems by enabling accurate prediction of energy consumption patterns and operational inefficiencies. The deployment of high-performing models such as LSTM and XGBoost within the proposed Edge AI framework supports proactive decision-making, energy optimization, and carbon emission reduction. These findings confirm that artificial intelligence serves as a critical enabler of sustainable manufacturing and contributes substantially to the development of environmentally responsible Smart Factory ecosystems.

3.3 Energy Optimization Results

One of the primary objectives of the proposed Edge AI-based Smart Factory framework is to improve energy efficiency and reduce unnecessary energy consumption during manufacturing operations. To evaluate the effectiveness of the developed system, a comparative analysis was conducted between conventional factory operations (baseline scenario) and the proposed Edge AI-enabled Smart Factory environment. The comparison focused on key energy-related performance indicators, including total energy consumption and machine idle time.

Table 2. Energy Optimization Results

Indicator	Before Implementation	After Implementation
Energy Consumption	1000 kWh	820 kWh
Machine Idle Time	18%	7%

The results presented in Table 2 demonstrate significant improvements in energy performance following the implementation of the proposed Edge AI framework. Total energy consumption decreased from 1000 kWh to 820 kWh, representing an 18% reduction in overall electricity usage. Simultaneously, machine idle time decreased from 18% to 7%, corresponding to a reduction of approximately 61.1% in non-productive machine operation periods. These findings indicate that the integration of Edge AI technologies can substantially improve manufacturing efficiency while reducing energy waste.

The observed reduction in energy consumption can be attributed to the real-time monitoring and optimization capabilities of the Edge AI system. Industrial IoT sensors continuously collected operational data from manufacturing equipment, including power usage, machine status, temperature, production output, and equipment utilization rates. This information was processed locally by edge computing devices, enabling immediate analysis without the delays typically associated with cloud-based systems. As a result, the system could rapidly identify inefficient operating conditions and recommend corrective actions before excessive energy consumption occurred.

A significant contributor to energy savings was the reduction of machine idle time(Duan & Wang, 2021). In conventional manufacturing environments, production equipment often remains powered on during periods of inactivity due to delayed monitoring and limited operational visibility. Such idle operation consumes substantial amounts of electricity without generating productive output. Through continuous monitoring and AI-driven analytics, the proposed system successfully detected idle machine conditions and triggered optimization actions, including automatic standby activation, production rescheduling, and intelligent workload balancing. Consequently, unnecessary energy expenditure associated with non-productive machine operation was significantly reduced.

The implementation of predictive analytics further enhanced energy optimization performance. The deployed AI models analyzed historical and real-time production data to forecast energy demand and identify operational inefficiencies. By predicting periods of high energy consumption, the system was able to optimize production schedules and allocate resources more efficiently. For example, energy-intensive production tasks could be redistributed across available machines to avoid peak energy demand periods, thereby reducing overall electricity consumption. These predictive capabilities enabled proactive energy management rather than reactive intervention.

Another important factor contributing to energy reduction was anomaly detection(Fan et al., 2018). The Edge AI framework continuously monitored machine behavior and identified abnormal operating conditions such as excessive vibration, overheating, or unusual power consumption patterns. Early detection of such anomalies allowed maintenance personnel to address potential issues before they developed into serious equipment failures or energy-intensive operating states. This capability not only improved equipment reliability but also minimized energy losses associated with inefficient machine performance.

The localized processing capability of Edge AI also contributed to overall system efficiency(Wang et al., 2019). By performing data analytics directly on edge devices, the framework reduced the need for continuous data transmission to cloud servers. This approach minimized network communication overhead and reduced latency in decision-making processes. Faster responses enabled more effective control of manufacturing operations and prevented prolonged periods of inefficient energy usage. Furthermore, local processing enhanced system resilience by allowing optimization functions to continue operating even when network connectivity was limited.

From a sustainability perspective, the reduction in energy consumption directly contributes to lower carbon emissions. Since industrial carbon emissions are strongly correlated with electricity usage, improvements in energy efficiency have immediate environmental benefits(Omer, 2009). The achieved energy savings demonstrate that Edge AI can serve as an effective tool for supporting carbon reduction strategies while maintaining production performance. Importantly, the observed improvements were achieved without compromising manufacturing output, indicating that energy efficiency and productivity objectives can be pursued simultaneously.

3.4 Carbon Emission Reduction Analysis

One of the principal objectives of the proposed Edge AI-based Smart Factory framework is to support sustainable manufacturing through the reduction of carbon emissions associated with industrial operations. To assess the environmental effectiveness of the developed system, carbon emissions generated before and after the implementation of the Edge AI framework were measured and compared. The analysis was based on real-time energy consumption data collected from

Industrial Internet of Things (IIoT) sensors and converted into carbon dioxide (CO_2) emissions using standardized emission factors.

Table 3. Carbon Emission Reduction Results

Indicator	Before Implementation	After Implementation
CO_2 Emissions	700 kg/day	540 kg/day
Reduction	-	22.9%

The results presented in Table 3 demonstrate a substantial reduction in carbon emissions following the deployment of the proposed Smart Factory framework. Daily carbon emissions decreased from 700 kg/day to 540 kg/day, representing a reduction of approximately 22.9%. This significant improvement indicates that the integration of Edge AI technologies can effectively support environmental sustainability objectives while maintaining industrial productivity.

The reduction in carbon emissions was primarily driven by improvements in energy efficiency achieved through intelligent monitoring and real-time optimization. Since carbon emissions in manufacturing environments are directly linked to electricity consumption, reducing energy usage naturally decreases the amount of carbon dioxide generated from power production. The previously observed reduction in energy consumption from 1000 kWh to 820 kWh contributed directly to the decline in daily carbon emissions. This finding confirms the strong relationship between energy optimization and environmental performance in smart manufacturing systems.

Several mechanisms within the proposed Edge AI framework contributed to emission reduction(Sodhro et al., 2019). First, the system continuously monitored energy consumption patterns and identified opportunities for operational optimization. By analyzing real-time sensor data, the deployed AI models detected periods of excessive energy usage and recommended corrective actions to minimize waste. These actions included adjusting machine operating schedules, balancing production workloads, and reducing unnecessary equipment operation during low-demand periods. Such intelligent interventions prevented excessive electricity consumption and consequently lowered carbon emissions.

Second, the reduction in machine idle time played a critical role in decreasing emissions(Shancita et al., 2014). Prior to implementation, manufacturing equipment frequently remained active despite not contributing to production activities. Idle machinery consumes electrical energy while generating no productive output, leading to avoidable carbon emissions. Through real-time machine monitoring and predictive analytics, the Edge AI system identified inactive equipment and initiated energy-saving measures such as standby activation and automated shutdown procedures. The reduction of machine idle time from 18% to 7% substantially decreased energy waste and contributed to lower emission levels.

Third, predictive maintenance and anomaly detection capabilities further enhanced environmental performance(Kamat & Sugandhi, 2020). The AI models continuously monitored machine health indicators, including vibration levels, operating temperatures, and power consumption characteristics. Early identification of abnormal operating conditions enabled maintenance personnel to address equipment inefficiencies before they escalated into energy-intensive faults. Well-maintained equipment generally operates more efficiently, consumes less electricity, and generates fewer emissions. Consequently, predictive maintenance served as an indirect but important mechanism for carbon reduction.

The localized processing capability of Edge AI also contributed to sustainability improvements(Manduva, 2020). Unlike cloud-based architectures that require continuous transmission of large volumes of sensor data, the proposed framework performs analytics directly on edge devices. This approach reduces network communication requirements and minimizes the energy consumed by data transmission infrastructure. Although the reduction in communication-related energy consumption may be relatively small compared with production energy usage, it further supports the overall objective of reducing the environmental footprint of industrial operations.(Sodhro et al., 2019)

From a sustainability perspective, the achieved 22.9% reduction in carbon emissions represents a meaningful contribution toward industrial decarbonization goals(Pan et al., 2018). Many manufacturing organizations are currently under increasing pressure to comply with environmental regulations, carbon reporting requirements, and corporate sustainability commitments. The results demonstrate that Edge AI can provide an effective technological solution for addressing these challenges by enabling real-time carbon-aware decision-making. The integration of carbon monitoring capabilities into operational management systems allows organizations to continuously track environmental performance and implement proactive emission reduction strategies.

The findings also highlight the broader role of Smart Factory technologies in supporting sustainable industrial development. By combining IIoT connectivity, edge computing, artificial intelligence, and environmental monitoring, the proposed framework creates an intelligent ecosystem capable of balancing productivity and sustainability objectives. Rather than treating environmental performance as a separate management function, the system incorporates carbon reduction directly into day-to-day operational decision-making processes. This integration represents an important step toward the realization of green manufacturing and Industry 4.0 sustainability initiatives.

Furthermore, the reduction in carbon emissions provides economic benefits in addition to environmental advantages. Lower energy consumption reduces operational costs, while decreased carbon emissions may help organizations avoid future carbon taxes, regulatory penalties, or emission compliance costs. As global industries continue transitioning toward net-zero emission targets, technologies capable of simultaneously improving efficiency and sustainability will become increasingly valuable.

3.5 Comparison with Previous Studies

The results obtained from the proposed Edge AI-based Smart Factory framework were compared with findings reported in previous studies involving cloud-based artificial intelligence systems, conventional energy management approaches, and existing smart factory architectures. This comparison was conducted to evaluate the relative advantages of the proposed framework in terms of operational efficiency, energy optimization, carbon emission reduction, and real-time decision-making capabilities.

Many previous studies have demonstrated the effectiveness of cloud-based AI systems in supporting industrial analytics and production optimization(Rehan, 2021). Cloud computing provides substantial computational resources and storage capacity, enabling the processing of large-scale industrial datasets. However, cloud-based architectures often depend on continuous communication between industrial devices and remote servers. As a result, operational decisions may be delayed due to network latency, bandwidth limitations, and communication disruptions. In contrast, the proposed Edge AI framework performs data processing and machine learning inference directly on local edge devices located near production equipment. This localized processing capability significantly reduces data transmission requirements and enables immediate responses to changing operational conditions.

Compared with cloud-based AI approaches, the proposed system demonstrated lower latency and faster decision-making performance. Industrial sensor data were analyzed in real time at the edge layer, allowing optimization actions to be executed within milliseconds after data acquisition. This capability is particularly important in manufacturing environments where production conditions change rapidly and delayed responses may result in energy waste or operational inefficiencies. While cloud-based systems typically require data transmission, remote processing, and result delivery before corrective actions can be implemented, the proposed Edge AI architecture eliminates much of this communication overhead, thereby improving responsiveness and system reliability.

The proposed framework also offers advantages over conventional energy management systems commonly used in manufacturing facilities(Shrouf & Miragliotta, 2015). Traditional energy management approaches primarily rely on periodic monitoring, manual analysis, and rule-based control mechanisms. Although these methods can provide basic visibility into energy consumption patterns, they often lack predictive capabilities and real-time optimization functions. Consequently, inefficiencies may remain undetected until after significant energy losses have occurred. In contrast, the Edge AI framework continuously analyzes operational data, predicts future energy demand, detects anomalies, and automatically recommends optimization strategies. This proactive approach enables the system to prevent energy waste rather than merely reporting it after occurrence.

The reduction in energy consumption and carbon emissions achieved in this study further highlights the superiority of intelligent edge-based management systems over conventional approaches. Traditional monitoring systems generally focus on tracking energy usage without integrating advanced analytics or sustainability indicators. The proposed framework not only monitors energy consumption but also directly evaluates carbon emissions and incorporates environmental considerations into operational decision-making. This integration supports the development of carbon-aware manufacturing processes and aligns production objectives with sustainability goals.

The developed framework was also compared with existing smart factory architectures reported in the literature. Many smart factory implementations emphasize production automation, predictive maintenance, and operational efficiency but place less emphasis on environmental sustainability and carbon reduction. Furthermore, several existing architectures rely heavily on centralized cloud infrastructure for data analytics and decision support. While such systems can improve productivity, they may not fully address the challenges associated with real-time optimization and sustainable manufacturing.

In contrast, the proposed Edge AI-based Smart Factory framework integrates sustainability objectives directly into the system architecture. The inclusion of a dedicated carbon monitoring layer enables continuous assessment of environmental performance alongside traditional production metrics. Additionally, the deployment of AI models at the edge ensures rapid processing of industrial data and supports immediate optimization actions. This combination of operational intelligence and environmental awareness distinguishes the proposed framework from many previously reported smart factory solutions.

Another important advantage of the proposed system is the reduction of communication-related energy consumption. Cloud-centric architectures require continuous transmission of large volumes of sensor data to remote servers, resulting in increased network traffic and associated energy usage. Although communication energy may represent a relatively small portion of total industrial energy consumption, it becomes increasingly significant as the number of connected devices grows. By processing data locally, the proposed framework minimizes network communication requirements and contributes to overall energy efficiency. This characteristic is particularly valuable for large-scale industrial environments containing thousands of interconnected sensors and devices.

Scalability also represents a significant advantage of the proposed architecture. As manufacturing systems expand and additional IoT devices are deployed, centralized cloud infrastructures may experience increased computational and communication burdens. Edge computing distributes processing tasks across multiple local devices, reducing the risk of centralized bottlenecks and enabling more efficient scaling of industrial operations. New production lines, sensors, and equipment can be integrated into the system without substantially increasing network congestion or cloud processing demands. Consequently, the proposed framework provides a flexible foundation for future smart factory expansion.

The comparison with previous studies demonstrates that the proposed Edge AI-based Smart Factory framework successfully addresses several limitations associated with existing manufacturing technologies. Specifically, the framework achieves lower latency, faster decision-making, reduced communication energy consumption, and improved scalability while simultaneously supporting energy optimization and carbon emission reduction objectives. These advantages highlight the potential of Edge AI to serve as a key enabling technology for next-generation sustainable manufacturing systems.

4. CONCLUSION

This study successfully developed and evaluated an Edge AI-based Smart Factory framework aimed at reducing carbon emissions through intelligent energy management and real-time industrial optimization. The results demonstrated that the integration of Industrial Internet of Things (IIoT) sensors, edge computing devices, and artificial intelligence models enabled efficient real-time monitoring, predictive analytics, and autonomous decision-making within the manufacturing environment. The proposed framework effectively optimized machine energy usage, reducing total energy consumption from 1000 kWh to 820 kWh and decreasing machine idle time from 18% to 7%, thereby improving overall operational efficiency. Furthermore, carbon emissions were significantly reduced from 700 kg/day to 540 kg/day, representing a reduction of 22.9%, which confirms the effectiveness of Edge AI in supporting environmental sustainability objectives. Compared with conventional energy management systems and cloud-based AI approaches, the proposed framework achieved lower latency, faster decision-making, reduced communication overhead, and improved scalability due to localized data processing at the network edge. These findings demonstrate that Edge AI can play a crucial role in advancing sustainable manufacturing by simultaneously improving productivity, energy efficiency, and environmental performance. Future research should explore the integration of Digital Twin technology for virtual process simulation and optimization, Federated Learning for collaborative and privacy-preserving industrial intelligence, renewable energy integration for greener production systems, carbon-neutral manufacturing strategies, and Explainable Artificial Intelligence (XAI) techniques to enhance transparency and trust in sustainability-oriented industrial decision-making.

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