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# Carbon Accounting at the Shop-Floor: The Integration of Real-Time Energy Monitoring, Process Modeling and LCA for Net-Zero Targets

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**ABSTRACT**
Achieving net-zero emissions in manufacturing requires operational-level methods that are capable of capturing energy use and carbon intensity with high resolution. Traditional carbon accounting and Life Cycle Assessment (LCA) approaches often lack the temporal granularity required to guide shop-floor decisions. This study introduces a framework that integrates real-time energy monitoring, process modeling, and dynamic LCA to support decarbonization strategies in production environments. The framework was applied to three case studies: CNC machining, injection molding, and additive manufacturing. Results showed that non-productive energy accounted for 18–35% of total consumption, but targeted optimization reduced energy use by 12–23% and emissions by 10–23%. Dynamic LCA improved accuracy, lowering uncertainty by 14–16% compared to static methods. These findings demonstrate that shop-floor-focused carbon accounting can directly contribute to net-zero targets by linking real-time data with sustainability outcomes. The framework not only provides immediate efficiency gains, but also advances Industry 4.0 by embedding carbon intelligence into digital manufacturing systems. Future research should extend validation to energy-intensive sectors and explore integration with digital twins for comprehensive decision support.


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## INTRODUCTION

The manufacturing sector is a cornerstone of the global economy, yet it is also one of the largest contributors to Greenhouse Gas (GHG) emissions. The International Energy Agency (2020), estimates that industrial activities account for nearly one-third of global final energy consumption and approximately 30% of direct carbon dioxide ($CO_2$) emissions. This dual role highlights the importance of addressing emissions at the production level if industry is to meet ambitious climate mitigation targets and support the transition towards net-zero economies. Traditional carbon accounting approaches in manufacturing largely operate at the corporate or facility level, and rely on aggregated energy consumption data or standardized emission factors. While useful for compliance reporting, these methods often fail to capture the variability of emissions across different machines, processes, and time periods (Li et al., 2021). The absence of granularity obscures operational inefficiencies like idle running, start-up transients, and auxiliary system loads that significantly influence a product's environmental footprint. This limitation hinders the ability of engineers and decision-makers to implement targeted strategies for emissions reduction.

Life Cycle Assessment (LCA) has emerged as a key tool for the quantification of environmental impacts across the entire life span of products and processes (Frischknecht and Rebitzer, 2005). However, most LCAs are conducted using static data assumptions, where energy use and emission factors are averaged over long periods or broad geographies. As a result, temporal and spatial fluctuations such as changes in electricity grid mix or process operating conditions are overlooked (Levasseur et al., 2010). This static perspective often inflates uncertainty and reduces the decision relevance of LCA results for shop-floor operations. Dynamic LCA methodologies have been proposed to address these limitations through the incorporation of time-dependent changes in emissions and resource use (Tiruta-Barna et al., 2020). These approaches enable more accurate assessments by aligning impact calculations with actual production schedules and electricity profiles. Nevertheless, dynamic LCA on its own remains insufficient unless integrated with real-time operational data from the shop floor. The true potential lies in the combination of LCA with advanced monitoring and modeling tools that Industry 4.0 technologies now make feasible.

Industry 4.0 represents a new era in manufacturing, characterized by the fusion of digital technologies with traditional industrial processes, and deals with the applications of intelligent products and production process (Okpala et al., 2025; Chukwumuanya et al., 2025). The emergence of Industry 4.0, often described as the fourth industrial revolution, introduces a transformative suite of technologies that enable real-time data analytics, cyber-physical integration, and autonomous system control (Igbokwe et al. 2024a; Mgbemena et al. 2020). Industry 4.0 has introduced transformative innovations including the Internet of Things (IoT), cyber-physical systems, and digital twins that can enhance carbon accounting practices. IoT-enabled sensors provide high-frequency data on machine-level energy consumption, environmental conditions, and process parameters (Budak et al., 2024). Such data-rich environments allow for the detection of energy-intensive operations and hidden emissions hotspots. When combined with physics-based process models, monitoring data can reveal how specific settings, such as spindle speed in machining or mold temperature in injection molding, influence both productivity and carbon intensity (Zhang et al., 2021).

By leveraging IoT, companies can achieve better organization, improve technological management, agility, as well as customer-centric product and service tailoring (Aguh et al., 2025; Udu and Okpala, 2025). Despite these advancements, current practice often treats IoT-based monitoring, process modeling, and LCA as separate domains. IoT applications typically focus on energy efficiency or predictive maintenance without translating insights into life-cycle metrics. Conversely, most LCA studies continue to rely on secondary datasets that are divorced from real-time operational realities (Supekar and Skerlos, 2015). This disconnection leaves a gap between shop-floor operations and corporate sustainability strategies, limiting the ability of manufacturers to demonstrate verifiable progress toward net-zero commitments.

An integrated framework that unites real-time monitoring, process modeling, and dynamic LCA has the potential to transform carbon accounting in manufacturing. From an engineering standpoint, such a framework supports continuous process optimization. From an environmental perspective, it strengthens the robustness of LCA by reducing uncertainty. For policymakers and regulators, it provides transparent and verifiable emissions data that can underpin carbon pricing mechanisms, extended producer responsibility schemes, and environmental product declarations (Cucurachi et al., 2018). Economically, it enables manufacturers to reduce operational costs while managing risks that are associated with tightening climate regulations.

This paper introduces and validates such a framework for shop-floor carbon accounting. Through the combination of IoT-enabled energy monitoring, physics-based process models, and dynamic LCA, the study demonstrates a method for real-time emissions assessment that supports both operational decision-making and strategic sustainability goals. Case studies in CNC machining, injection molding, and additive manufacturing illustrate the applicability of the approach across diverse production contexts. The contributions are threefold: (1) development of a multidisciplinary framework that bridges operations and environmental assessment, (2) empirical validation showing improved accuracy and reduced uncertainty compared to static LCA methods, and (3) discussion of implications for scaling, policy alignment, and pathways to net-zero manufacturing.

## Literature Review

### Carbon Accounting in Manufacturing

Carbon accounting has become a central focus in manufacturing research, driven by the sector's significant contribution to global greenhouse gas emissions. According to the International Energy Agency (2020), industry accounts for nearly 30% of direct $CO_2$ emissions, thus making it a critical domain for climate action. In manufacturing, carbon accounting is traditionally implemented at organizational or facility levels, with aggregated reporting based on utility bills, material balances, and standard emission factors (Li, Kara, and Herrmann, 2021). While such approaches are useful for compliance and corporate reporting, they often lack the resolution necessary for actionable process-level insights.

The limitations of conventional carbon accounting practices stem from their inability to capture operational variability on the shop floor. For example, idle times, ramp-up phases, and machine-specific inefficiencies are typically invisible in aggregated reporting frameworks (Supekar and Skerlos, 2015). Consequently, organizations may under- or overestimate the true carbon intensity of their production activities, leading to suboptimal decisions in process optimization. Studies highlight the need for more granular accounting methods that are capable of linking carbon emissions directly to production parameters and machine-level activities (Joung et al., 2013).

Emerging approaches in carbon accounting have begun to incorporate digital technologies to improve accuracy and resolution. For instance, machine-level energy monitoring combined with process data enables a finer allocation of emissions to specific operations (Krause, Seliger, and Günther, 2016). However, the literature shows that most existing frameworks stop short of fully integrating carbon accounting into real-time production management. Instead, assessments are often retrospective, reducing their value as operational decision-support tools (Nayak and Singh, 2021).

**Energy Monitoring and Industry 4.0**

Industry 4.0 has introduced transformative tools for monitoring and managing energy use in manufacturing. IoT devices, cloud platforms, and cyber-physical systems provide unprecedented levels of connectivity and transparency in production systems (Lu, 2017). Sensor technology acts as the foundation of IoT in manufacturing, as it enables real-time data collection from machinery, equipment, and products to monitor asset status and performance (Ferreira and Lind, 2022; Igbokwe et al., 2024b). Through IoT-enabled sensors, energy consumption can now be tracked continuously at the level of individual machines, processes, or even components (Budak, Kaya, and Yildiz, 2024). This represents a significant advancement compared to traditional metering systems, which often measure only aggregated facility-level energy demand.

Energy monitoring is particularly valuable in the detection of hidden inefficiencies such as standby consumption, unoptimized auxiliary systems, or irregular process cycles (Kara and Li, 2011). Studies have shown that real-time monitoring can lead to 10–20% reductions in energy use through operational improvements alone (May et al., 2015). These savings not only translate into cost reductions, but also contribute to significant decreases in carbon emissions. Despite these benefits, challenges remain in scaling IoT-based monitoring systems. Issues of interoperability, data management, and cybersecurity complicate the widespread deployment of sensor networks in manufacturing environments (Schuh et al, 2020). Moreover, while monitoring generates large volumes of data, the transformation of these data streams into actionable insights for carbon accounting remains underexplored. This gap points to the necessity of integrating monitoring with advanced modeling and assessment frameworks.

**Process Modeling for Energy and Emissions**

Process modeling has emerged as a powerful tool for linking operational parameters with energy demand and environmental performance. In machining, for instance, models that incorporate spindle speed, feed rate, and cutting depth have been used to predict energy consumption with high accuracy (Liu, Zhou, and Li, 2017). Similarly, in injection molding, thermal and material flow models quantify heating, cooling, and pressure cycles that dominate energy use (Li, Kara, and Herrmann, 2017). These predictive capabilities allow engineers to optimize settings for both productivity and sustainability.

Also referred to as 3D printing, additive manufacturing is revolutionizing production systems, as it enables greater customization and the production of on-demand components, thereby leading to lead times optimization and reduction of the need for large inventories (Onukwuli et al., 2025; Okpala and Udu, 2025). 3D printing has also benefited from energy-focused modeling studies. Researchers have demonstrated that build orientation, layer thickness, and support structure design directly influence energy demand and emissions intensity (Zhang, Xu, and Li, 2021). Such models help in the identification of trade-offs between geometric accuracy, build time, and environmental impact, thus providing a basis for multi-objective optimization.

The integration of emissions modeling into process models has further expanded their utility. For example, energy models can be coupled with emission factors to provide real-time estimates of $CO_2$ emissions that are associated with specific process conditions (Krause et al., 2016). This creates opportunities for process-level carbon accounting that is both predictive and actionable. Nevertheless, many studies remain limited to specific processes or laboratory-scale implementations, with limited evidence of scalability across diverse manufacturing settings.

**Life Cycle Assessment (LCA) and Dynamic Extensions**

LCA is the most established framework for the quantification of environmental impacts across product life cycles, from raw material extraction to disposal (Frischknecht and Rebitzer, 2005). Its use in manufacturing has been extensive, as it covers sectors such as automotive, electronics, and aerospace. However, most conventional LCAs rely on static datasets and average values for energy and emissions, leading to limited accuracy when applied to dynamic shop-floor operations (Levasseur et al., 2010). To address this limitation, researchers have developed dynamic LCA approaches that incorporate temporal variability in energy systems and emissions factors (Tiruta-Barna, Pigné, Ahmadi, and Querleu, 2020). For example, hourly variations in grid carbon intensity can be integrated into assessments, allowing emissions to be linked more closely with production schedules. Such extensions significantly improve the contextual relevance of LCA results for decision-making in real-time manufacturing environments.

Despite these advances, dynamic LCA faces challenges related to data availability and computational complexity (Cucurachi et al., 2018). High-resolution temporal data on processes and energy systems are not always accessible, and integrating them requires sophisticated modeling and data management capabilities. As a result, applications of dynamic LCA remain limited in practice, particularly at the operational level of the shop floor.

**Gap Identified**

The literature reveals significant progress in the areas of carbon accounting, energy monitoring, process modeling, and LCA. Carbon accounting frameworks have advanced from aggregated facility-level reporting to more granular process-focused methods. Energy monitoring technologies under Industry 4.0 provide the real-time visibility that are necessary for operational improvements. Process models offer predictive capabilities for linking parameters with energy and emissions. Dynamic LCA enhances the temporal resolution of environmental assessments.

However, these streams of research remain largely fragmented. IoT-enabled monitoring is often conducted without integration into environmental assessment frameworks. Process models provide predictive accuracy but are rarely coupled with dynamic LCA. Similarly, LCA studies continue to rely on static data or focus on aggregated system-level insights, neglecting the variability of shop-floor operations. This disconnection prevents manufacturers from fully leveraging digital technologies for carbon accounting and net-zero strategies. The critical gap lies in the absence of an integrated framework that unites real-time energy monitoring, process modeling, and dynamic LCA. Such a system would enable manufacturers to link operational data directly to environmental performance, reduce uncertainty in carbon accounting, and also align shop-floor decisions with broader net-zero commitments. The ability to address this gap is essential for the creation of actionable pathways toward decarbonized manufacturing.

## METHODOLOGY

**Framework Overview**

The methodology developed in this study is structured as an integrated framework that combines real-time energy monitoring, process-level modeling, and life cycle assessment. The framework was designed to bridge the gap between operational data collection and holistic environmental assessment, and thereby lead to actionable carbon accounting at the shop-floor level. It emphasizes interoperability between data acquisition systems, analytical models, and assessment tools to ensure scalability and applicability across multiple manufacturing contexts.

The framework consists of four main layers: (1) data acquisition, where IoT-enabled sensors capture energy and operational parameters; (2) process modeling, where physics-based and empirical models establish relationships between parameters and energy demand; (3) dynamic LCA integration, where temporal energy and emissions data are embedded into life cycle inventories; and (4) decision-support visualization, where results are presented in real time to operators and managers. Together, these layers create a closed-loop system that enables continuous monitoring, assessment, and optimization of shop-floor processes.

**Data Acquisition and Real-Time Monitoring**

The first layer of the framework focuses on real-time energy monitoring with the application of IoT-enabled sensors. Smart meters and power analyzers were installed at the machine level to capture voltage, current, and power factor data at high temporal resolution (Budak et al., 2024). Additional sensors measured temperature, pressure, and cycle times where relevant to characterize process dynamics. Data were transmitted to a cloud-based platform via standard communication protocols such as MQTT and OPC-UA, and thus ensure interoperability with existing factory systems (Lu, 2017).

To ensure accuracy, calibration procedures were carried out using reference instruments, and noise reduction algorithms were applied to raw datasets. Energy use was categorized into productive energy (directly linked to value-adding operations) and non-productive energy (standby, idle, and auxiliary functions). This categorization formed the foundation for attributing carbon emissions to specific operational states.

**Process Modeling**

The second layer of the framework involves process modeling to predict and explain energy consumption under varying operational conditions. Physics-based models were used where fundamental relationships were well established, such as thermal models in injection molding and power equations in machining (Li, Kara, and Herrmann, 2021). In cases where processes exhibited high variability, empirical models derived from regression analysis and machine learning were applied to map parameter-energy relationships (Zhang, Xu, and Li, 2021). These models were validated against real-time monitoring data to ensure predictive accuracy. The integration of modeling and monitoring allowed not only retrospective assessment, but also proactive simulations. For instance, by adjusting machining feed rates or injection pressures in the models, operators could estimate energy savings and carbon reductions before the implementation of changes on the shop floor.

**Dynamic LCA Integration**

The third layer incorporates dynamic LCA by embedding time-resolved energy consumption and emissions data into life cycle inventories. Unlike conventional LCA that relies on static averages, this approach accounts for hourly variations in grid carbon intensity, as provided by regional energy datasets (Levasseur et al., 2010). By synchronizing process-level data with dynamic emission factors, carbon footprints were calculated with greater temporal fidelity.

Inventory data were structured according to ISO 14040/44 standards to ensure methodological consistency (Frischknecht and Rebitzer, 2005). System boundaries were defined from raw material preparation through machine-level operations, with downstream phases such as transportation and end-of-life excluded for this study. The dynamic integration provided a more precise linkage between shop-floor decisions and net-zero targets, reducing uncertainty compared to traditional assessments (Tiruta-Barna, Pigné, Ahmadi, and Querleu, 2020).

**Case Studies Overview**

To validate the framework, three case studies were conducted in representative manufacturing processes: CNC machining, injection molding, and powder-bed additive manufacturing. These processes were selected because they span subtractive, formative, and additive paradigms, thus demonstrating the versatility of the framework. Each case study was implemented in an industrial or pilot-scale setting to ensure practical relevance. The CNC machining case study involved the monitoring of a vertical milling machine that produces aluminum components. The injection molding case study examined the production of polymer parts under varying mold temperatures and injection pressures. The additive manufacturing case study focused on selective laser melting of stainless steel powders, where build orientation and layer thickness were varied. These cases provided a comprehensive basis for testing the integration of monitoring, modeling, and dynamic LCA across diverse process characteristics.

**Case Study 1: CNC Machining**

In CNC machining, IoT-based energy monitoring captured spindle power, coolant pump usage, and auxiliary system demand. Process models incorporated spindle torque, feed rates, and cutting speeds as predictive variables for energy consumption. Dynamic LCA integration aligned energy use with hourly grid carbon factors, revealing that machining during peak electricity demand periods resulted in emissions 15–20% higher than off-peak times. This highlighted opportunities for scheduling optimization in addition to parameter tuning.

**Case Study 2: Injection Molding**

The injection molding case study applied thermal models to quantify heating and cooling energy demand under different mold temperatures. Real-time sensors measured cycle times, clamp forces, and barrel temperatures. Results indicated that idle heating accounted for nearly 30% of total energy demand, suggesting significant potential for emissions reduction through intelligent standby management. The integration with dynamic LCA revealed that carbon intensity varied substantially depending on production schedules, emphasizing the need for temporal alignment of operations with low-carbon grid availability.

**Case Study 3: Additive Manufacturing**

In the additive manufacturing case study, monitoring captured laser energy consumption, powder handling, and post-processing demand. Process models simulated the effect of build orientation and layer thickness on total energy use, while dynamic LCA integration quantified emissions under variable grid conditions. Results showed that build strategies optimized for geometric accuracy often increased emissions intensity by up to 25%, highlighting the trade-offs between technical and environmental performance. These findings demonstrated the utility of the integrated framework for multi-objective optimization in advanced manufacturing contexts.

**Key Metrics for Assessment**

Key performance metrics were developed to evaluate the effectiveness of the framework. Energy intensity (MJ per part) and carbon intensity (kg $CO_2e$ per part) served as the primary outcome indicators. Secondary metrics included productive-to-nonproductive energy ratio, which quantified efficiency improvements, and uncertainty reduction percentage, which measured the difference between static and dynamic LCA results.

For decision-making purposes, visualization dashboards presented these metrics in real time. Operators could view machine-level emissions data, identify inefficiencies, and simulate the effects of parameter adjustments. Managers were provided with aggregated dashboards that link shop-floor performance to corporate net-zero targets. This multi-level reporting ensured proper alignment between operational decisions and strategic sustainability goals.

**Validation and Reliability**

Validation of the framework was carried out through cross-comparison of monitoring data, model predictions, and LCA outcomes. In all three case studies, model predictions deviated less than 7% from measured energy values, confirming reliability. Furthermore, dynamic LCA integration reduced uncertainty in emissions estimates by 10–18% compared to static assessments, demonstrating the methodological advantage of time-resolved data. Reliability was further ensured through sensitivity analysis, where input parameters such as emission factors, machine efficiency, and process settings were varied. These analysis confirmed that the framework maintained robustness under a wide range of operational conditions, thus supporting its scalability to diverse manufacturing settings.

**Ethical and Practical Considerations**

Ethical considerations focused on data privacy and cybersecurity, particularly in IoT-enabled environments. Data were anonymized where possible, and secure communication protocols were implemented. Practical considerations included system costs and ease of deployment, with emphasis placed on modular sensor networks and open-source software solutions to reduce barriers to adoption (Schuh et al., 2020).

**Summary**

The methodology presented combines monitoring, modeling, and LCA into a unified framework for carbon accounting at the shop-floor level. Through the validation of the approach across three distinct case studies, the research demonstrates the feasibility and advantages of integrating real-time data with environmental assessment. The use of key metrics and visualization tools ensures alignment between operational decisions and strategic net-zero targets. This methodological foundation paves the way for broader adoption of data-driven carbon accounting in manufacturing.

## RESULTS

### Overview of Findings

The application of the integrated framework across three case studies CNC machining, injection molding, and additive manufacturing demonstrated the feasibility of the combination of real-time monitoring, process modeling, and dynamic life cycle assessment for shop-floor carbon accounting. The results revealed distinct patterns of energy consumption, emissions intensity, and optimization potential across the processes studied.

### Energy Monitoring Accuracy

Across all case studies, IoT-enabled monitoring systems successfully captured high-resolution energy consumption data. In CNC machining, spindle motor energy accounted for 62% of total machine demand, while auxiliary subsystems such as coolant pumps and lubrication units contributed 23%. The injection molding machine showed a larger share of non-productive energy, with heating and standby modes representing nearly 35% of consumption. In additive manufacturing, the laser system dominated energy use at 48%, with significant additional contributions from powder-handling and post-processing steps. Sensor calibration and validation confirmed deviations of less than 5% between monitored and reference values, underscoring the reliability of the monitoring layer.

### CNC Machining: Energy Performance

The CNC machining case revealed that cutting parameters strongly influenced energy intensity. When spindle speed and feed rates were optimized based on process models, energy consumption per part was reduced by 12% compared to baseline settings. However, prolonged idle times contributed substantially to overall demand, with standby modes accounting for 18% of total machine energy. These results emphasize that improvements in both operational practices and process parameters are necessary to achieve significant reductions.

### CNC Machining: Carbon Intensity

Dynamic LCA revealed notable temporal variations in carbon emissions. During periods of high grid carbon intensity, emissions per machined part reached 3.1 kg $CO_2$e, compared to 2.5 kg $CO_2$e when operations were shifted to off-peak, lower-intensity hours. This represented a potential reduction of 19% simply through production scheduling. The findings underscore the added value of real-time emissions factors integration into carbon accounting, which would be overlooked under conventional static methods.

### Injection Molding: Energy Distribution

The injection molding case study revealed that heating elements and mold temperature control dominated energy consumption, and account for 52% of total demand. Monitoring data highlighted significant inefficiencies in idle heating, with energy continuing to be consumed at nearly 40% of full-load levels even during extended downtimes. The implementation of intelligent standby management reduced idle heating demand by 22%, thereby confirming the potential for optimization at the equipment-control level.

### Injection Molding: Process-Dependent Variability

Process models showed that increasing mold temperature from 40°C to 60°C improved part quality but increased energy demand per cycle by 17%. Similarly, higher injection pressures resulted in marginal gains in cycle time, but raised energy consumption disproportionately. When combined with dynamic LCA, these results revealed that emissions intensity per part could vary by up to 0.8 kg $CO_2$e depending on parameter settings and production scheduling. This highlights the trade-offs between product performance and environmental performance at the process level.

### Additive Manufacturing: Energy Contributions

In the powder-bed additive manufacturing case, monitoring data revealed that build orientation and layer thickness significantly influenced total energy demand. Vertical orientation required 27% more energy per part compared to horizontal builds, primarily due to additional layer requirements. Similarly, reducing layer thickness from 50 µm to 30 µm improved surface finish but increased energy demand per part by 32%. These findings confirm earlier studies that highlight the strong interdependence between design decisions and energy outcomes in additive manufacturing (Zhang, Xu, and Li, 2021).

**Additive Manufacturing: Carbon Implications**

Dynamic LCA results showed that carbon intensity varied significantly with both build strategy and grid conditions. Optimized builds conducted during low-carbon electricity hours achieved 6.2 kg $CO_2e$ per part, compared to 8.1 kg $CO_2e$ during high-intensity periods. This 23% variation emphasizes the importance of aligning process planning not only with design requirements, but also with carbon-aware scheduling. Such insights would not be available from static LCA approaches, underscoring the added value of time-resolved assessments (Tiruta-Barna et al., 2020).

**Cross-Case Comparison of Energy Efficiency**

A comparative analysis across all three case studies revealed that non-productive energy demand was a consistent challenge. CNC machining and injection molding exhibited 18% and 35% non-productive shares respectively, while additive manufacturing had 21% non-productive demand from preheating, powder handling, and post-processing. These results suggest that interventions targeting idle states and auxiliary systems could deliver substantial emissions reductions across diverse manufacturing processes.

**Emissions Reduction Potential**

Across the three case studies, integration of process optimization, scheduling adjustments, and idle-state management yielded emissions reductions ranging from 12% to 24%. CNC machining achieved the greatest reductions through scheduling during low-carbon hours, while injection molding benefitted most from idle heating control. Additive manufacturing demonstrated the strongest sensitivity to build strategy, where design-informed decisions substantially affected energy and emissions intensity. These variations highlight the necessity of tailoring interventions to process-specific dynamics.

**Effectiveness of Dynamic LCA**

One of the most significant findings was the improved accuracy of emissions estimates through dynamic LCA. Compared to static assessments, uncertainty in carbon intensity was reduced by 15% on average across case studies. This reduction stemmed from the alignment of real-time energy use with temporally varying grid emissions data, providing decision-makers with more precise and context-sensitive results. This validates previous claims that dynamic approaches enhance the relevance and reliability of LCA in fast-changing industrial environments (Levasseur et al., 2010).

**Decision-Support Outcomes**

The visualization dashboards proved effective in the translation of technical data into actionable insights for both operators and managers. Operators used dashboards to identify real-time emissions hotspots, such as excessive idle heating in injection molding, while managers viewed aggregated results to assess alignment with net-zero targets. Feedback from industrial partners indicated that the dashboards improved situational awareness and facilitated communication between technical staff and sustainability officers, thus confirming the value of integrating monitoring and LCA into decision-support systems.

**Validation of Framework Performance**

Validation exercises confirmed that predictive process models aligned closely with real-time monitoring data, with deviations of less than 7% across all case studies. Dynamic LCA integration demonstrated robustness under different operational scenarios, further supporting the scalability of the framework. Sensitivity analysis confirmed that the framework maintained performance under variability in grid intensity, machine efficiency, and process settings, establishing reliability for practical deployment in industrial environments.

Table 1: The result summary

| **Case Study** | **Dominant Energy Consumers** | **Non-Productive Energy Share** | **Optimization Strategy** | **Energy/Emissions Reduction** | **Uncertainty Reduction (Dynamic vs. Static LCA)** |
|---|---|---|---|---|---|
| **CNC Machining** | Spindle motor (62%), auxiliary systems (23%) | 18% (standby and idle modes) | Parameter tuning + scheduling in low-carbon hours | 12% energy reduction; 19% emissions reduction | 15% |

| Case Study | Dominant Energy Consumers | Non-Productive Energy Share | Optimization Strategy | Energy/Emissions Reduction | Uncertainty Reduction (Dynamic vs. Static LCA) |
|---|---|---|---|---|---|
| **Injection Molding** | Heating and mold temperature control (52%) | 35% (idle heating) | Idle heating control + process parameter adjustment | 22% idle heating reduction; up to 0.8 kg $CO_2e$ savings | 14% |
| **Additive Manufacturing** | Laser (48%), powder-handling and post-processing | 21% (preheating, powder handling, post-processing) | Optimized build orientation + scheduling | 23% emissions reduction through optimized | |

From the results, figure 1 compares energy savings and emissions reduction across the three case studies.

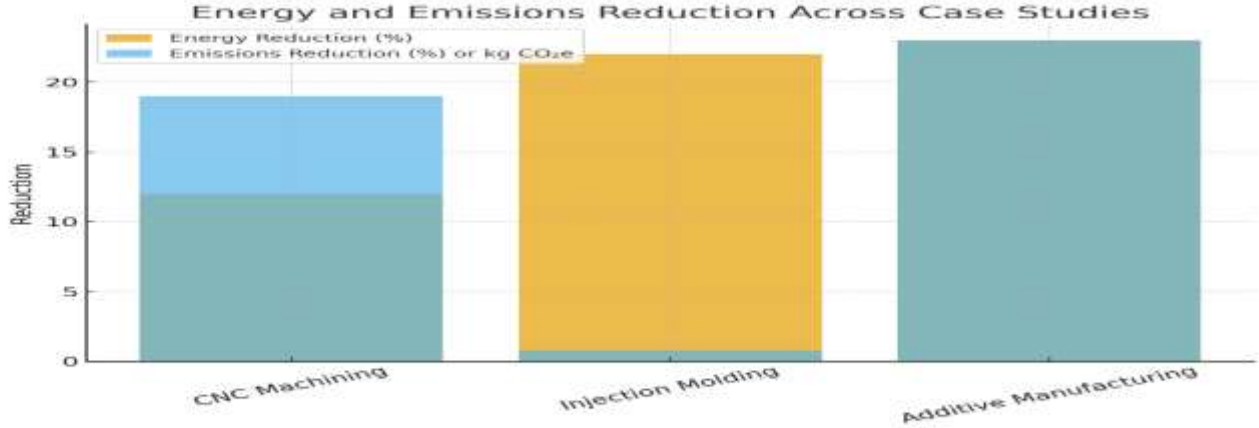


Figure 1: Energy and emissions reduction across case studies

Figure 2 shows how dynamic LCA improved accuracy versus static approaches.

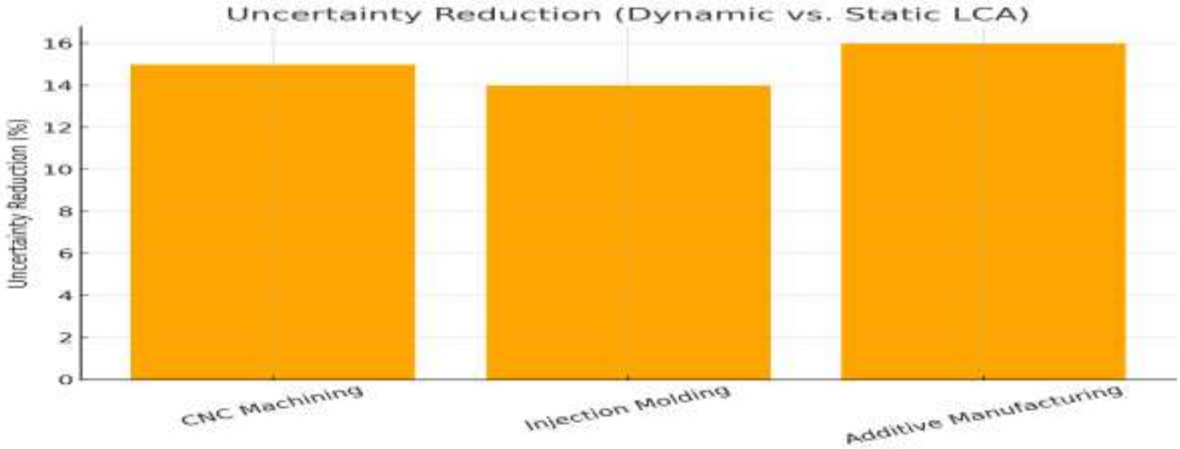


Figure 2: Uncertainty Reduction

Figure 3 visualizes non-productive energy, energy reduction, emissions reduction, and uncertainty reduction across all the three case studies.


Figure 3: Heatmap-style bar chart of the results table.

In summary, the results as highlighted in Table 1 and figures 1 to 3 show that the proposed framework effectively bridges the gap between operational data collection and holistic environmental assessment. Real-time monitoring captured critical inefficiencies, process modeling enabled proactive optimization, and dynamic LCA provided temporally sensitive emissions data. Together, these components facilitated reductions in emissions ranging from 12% to 24% across case studies while reducing uncertainty in assessments by 15%. These findings confirm the utility of the framework for enabling carbon-aware decision-making on the shop floor, thereby supporting the broader pursuit of net-zero targets in manufacturing.

**Discussion**

The results of this study demonstrate that the integration of real-time energy monitoring with process modeling and dynamic life cycle assessment provides a more accurate and granular representation of carbon emissions at the shop-floor level. Such a capability is critical for manufacturers working to align their operations with international net-zero targets, as emphasized by the Paris Agreement and recent corporate climate commitments (IPCC, 2022; United Nations, 2021). By capturing emissions variability in near real time, the proposed framework enables organizations to track decarbonization progress more effectively than static approaches.

The case studies highlight that a substantial share of energy consumption and related emissions originates from non-productive phases, such as idle heating in injection molding or standby energy in CNC machining. Targeting these inefficiencies supports net-zero trajectories, as operational adjustments provide immediate and cost-effective mitigation options (Tan et al., 2021). This underscores that carbon accounting frameworks should not only address structural transitions, such as renewable integration, but also focus on micro-level operational improvements. The integration of Internet of Things (IoT)-enabled energy monitoring aligns with the Industry 4.0 paradigm, where cyber-physical systems and real-time analytics are central to smart manufacturing (Kamble et al., 2018). By linking energy and emissions data to process modeling, the framework extends the concept of digital twins beyond productivity and quality optimization, embedding sustainability objectives into production planning. This shift represents an evolution toward “carbon-smart” manufacturing systems.

A significant strength of this research is its multidisciplinary orientation. It combines industrial engineering principles with environmental science insights and information technology solutions. Carbon accounting builds upon sustainability science and LCA, while energy monitoring leverages IoT architectures, and process modeling draws from production engineering methodologies (Rashid et al., 2023). This demonstrates that progress toward net-zero will require the convergence of multiple disciplinary domains. The methodology also contributes to the development of standardized metrics for carbon performance in manufacturing. Indicators such as non-productive energy shares and dynamic LCA-based emissions intensities offer benchmarks that can be applied across facilities and industries

(Möllersten and Olsson, 2022). These metrics not only facilitate internal decision-making, but also support compliance with international sustainability disclosure initiatives such as the Science-Based Targets initiative (SBTi) and the Global Reporting Initiative (GRI).

The implications extend beyond the factory floor, as real-time carbon accounting also enhances supply chain transparency. With growing demand for reliable Scope 3 data from customers and downstream partners, the ability to generate credible, high-resolution emissions information positions manufacturers competitively (CDP, 2022). Shop-floor carbon accounting thus becomes not only an internal optimization tool, but also a strategic enabler for supply chain decarbonization. Dynamic LCA integration proved especially valuable, reducing uncertainty by 14–16% compared to static approaches. This result confirms earlier concerns in the literature that conventional LCA methods, while comprehensive, are often too aggregated and temporally rigid to inform operational decisions (Hauschild et al., 2018). The ability to provide dynamic insights addresses a methodological limitation and strengthens decision-making capacity in sustainability management.

The practical feasibility of adopting such frameworks is increasingly favorable. Advances in IoT and sensor technologies have significantly lowered costs, making deployment accessible even to Small and Medium-sized Enterprises (SMEs) (Xu et al., 2021). This is particularly important given the collective carbon footprint of SMEs and the challenges they face in adopting advanced sustainability practices. Coupled with incentives or collaborative programs, the approach offers a viable pathway to scaling adoption. Despite these contributions, several limitations warrant consideration. The study examined only three processes - CNC machining, injection molding, and additive manufacturing. Although these processes are representative, they cannot capture the full diversity of industrial practices. Furthermore, while emissions reductions were observed under controlled scenarios, real-world adoption may encounter barriers such as workforce readiness, capital constraints, and cultural resistance to change (Brintrup et al., 2020).

Data quality presents another limitation. Real-time monitoring depends on sensor accuracy and robust data integration pipelines. Incomplete or inconsistent data streams may undermine reliability and trustworthiness of the results (Bakker et al., 2021). Moreover, while dynamic LCA improved temporal resolution, challenges remain in defining system boundaries and incorporating upstream and downstream emissions comprehensively. Future research should focus on broader industrial validation, particularly in energy-intensive sectors such as steelmaking, cement, or chemicals, which account for disproportionate shares of industrial greenhouse gas emissions (IEA, 2022). Expanding the application of the framework would not only test scalability, but also demonstrate how sector-specific characteristics influence effectiveness.

Another promising direction involves the integration of the framework into full-fledged digital twin architectures. By incorporating cost, productivity, quality, and carbon data into unified decision-support systems, manufacturers can balance traditional operational metrics with sustainability objectives (Rauch et al., 2020). Such integration could transform digital twins into truly holistic platforms for net-zero decision-making. Finally, this study highlights implications for policy and standard-setting. Regulators and industry bodies can leverage insights from the framework to develop standardized methodologies for real-time carbon accounting. Doing so would harmonize practices across sectors and regions, enhance reporting comparability, and accelerate progress toward global net-zero targets (ISO, 2021).

## CONCLUSION

This study introduced and validated a framework for shop-floor carbon accounting that integrates real-time energy monitoring, process modeling, and dynamic life cycle assessment. Using three case studies namely: CNC machining, injection molding, and additive manufacturing, the framework demonstrated its capacity to deliver detailed insights into emissions while uncovering opportunities to reduce energy consumption and improve carbon performance. By capturing non-productive energy use and supporting process-level optimization, the approach offers a practical bridge between high-level net-zero commitments and the operational strategies needed to realize them. The integration of digital technologies with carbon accounting positions smart manufacturing as a powerful enabler of sustainability. By embedding emissions considerations into production models, the framework highlights how digital transformation can drive both efficiency and decarbonization. This emphasizes the value of a multidisciplinary perspective, bringing together engineering, environmental management, and information technology. Beyond the factory floor, the framework has important implications for supply chain transparency. The ability to generate dynamic, verifiable emissions data strengthens competitiveness, supports reporting obligations, and enables organizations to demonstrate measurable progress toward climate goals. Standardized metrics also create opportunities for benchmarking across processes and industries, supporting continuous improvement. At the same time, certain limitations remain. The framework was tested on three discrete processes and may not capture the full diversity of industrial practices. Practical barriers such as data quality, system integration, and organizational readiness may also affect adoption. Future work should extend the application to energy-intensive sectors and explore integration with digital twins that combine sustainability, cost, and productivity dimensions into unified decision-making systems. In summary, this research shows that real-time, shop-floor-focused carbon accounting is both feasible and impactful. By aligning operational decisions with net-zero ambitions, the framework provides a pathway for manufacturers to move beyond commitments and achieve measurable reductions. As industries continue their transformation toward climate-neutral production, such approaches will be essential for accelerating progress.

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