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Article

Carbon Reduction Pathways for Manufacturing Enterprises Under Digital Monitoring Systems

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Abstract: This study examines how digital monitoring systems, including IoT sensing and automated carbon dashboards, support carbon reduction in manufacturing enterprises. The analysis focuses on 62 factories across electronics, machining, and chemical industries. Results show that real-time carbon tracking reduced energy waste by 12%, while automated equipment scheduling achieved an additional 9% reduction. Process-level carbon mapping also helped companies detect high-emission segments and optimize production planning. The findings demonstrate that digital tools significantly enhance carbon visibility and enable data-driven sustainability strategies.

Keywords: carbon monitoring; digital sustainability; manufacturing emissions; IoT tracking; energy optimization

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1. Introduction

Manufacturing is widely recognized as a major source of global greenhouse gas emissions, and reducing emissions has become an essential objective for governments and enterprises seeking to achieve long-term climate commitments [1]. In recent years, digital technologies-including industrial IoT, online monitoring platforms, and data-driven decision systems-have been increasingly viewed as enablers of cleaner and more efficient production [2]. Empirical evidence from national- and industry-level datasets shows that the relationship between digitalization and emissions is non-linear: while initial stages of digital adoption may increase energy consumption due to equipment upgrades and additional data-processing needs, deeper digital integration tends to produce measurable reductions in energy use and carbon emissions [3]. Similar findings have been reported across countries with varying industrial structures, suggesting that the carbon impact of digitalization depends not only on technological capability but also on how digital tools are embedded within production systems and regulatory environments [4]. At the factory level, real-time monitoring of energy and carbon has become central to low-carbon manufacturing strategies. IoT sensors, smart meters, and equipment-level data collectors enable factories to record energy use at short intervals, identify abnormal operating patterns, and locate machine-level inefficiencies with greater accuracy [5]. Case studies in electronics, machining, and other discrete manufacturing sectors show that these systems help reduce standby losses, improve maintenance planning, and enhance equipment utilization [6]. Recent developments further integrate online monitoring with automated carbon accounting modules, enabling factories to generate continuous emission profiles instead of relying solely on periodic reporting [7]. Digital twins and other cyber-physical simulation models offer additional opportunities by allowing manufacturers to test alternative production plans, evaluate process parameters, and optimize scheduling under energy constraints [8]. However, multiple reviews indicate that many digital systems remain limited to data visualization, while critical operational decisions-such as determining optimal time windows for running high-load equipment-often rely on manual judgment rather than automated optimization algorithms [9].

Beyond the technical perspective, research in sustainable operations emphasizes that digitalization produces meaningful environmental gains only when it is combined with systematic process-improvement frameworks. Recent evidence shows that integrating digital monitoring with lean-based approaches can reduce material waste, enhance process visibility, and strengthen continuous improvement cycles in manufacturing [10]. Such studies highlight that digital tools must support actionable decision-making-such as anomaly-driven control, dynamic load adjustment, and process-level optimization-rather than functioning solely as data-collection platforms. This integrated perspective also aligns with findings from broader sustainability literature, which stresses that effective carbon reduction requires coupling real-time information with mechanisms that modify production behavior at the equipment and process levels [11]. Despite these advances, significant research gaps remain. First, many existing studies rely on aggregated regional or sector-level datasets, which are useful for identifying macro trends but lack the granularity needed to evaluate how digital monitoring affects emissions within factories or at the machine level [12]. Second, factory-level research is often limited to one or two case sites, making it difficult to generalize findings across industries with distinct process characteristics, operational constraints, and equipment mixes [13,14]. Third, while substantial attention has been devoted to data acquisition and visualization technologies, relatively few studies link real-time monitoring with automated scheduling, anomaly-driven energy adjustments, or process-level carbon mapping capable of supporting detailed production planning [15]. Finally, there is a lack of large-sample, multi-industry evidence examining how integrated digital monitoring systems perform under actual operating conditions.

This study analyzes 62 factories across multiple industries that have adopted integrated digital monitoring systems combining IoT sensing, automated carbon dashboards, and equipment-scheduling modules. The analysis focuses on three operational mechanisms through which digital monitoring can reduce carbon emissions: (1) decreasing energy waste through real-time anomaly detection, (2) lowering emissions by using automated scheduling to optimize the operation of high-load equipment, and (3) identifying high-emission process segments through detailed carbon mapping to support production planning. By drawing on a large and diverse sample, this study provides empirical evidence on how digital monitoring improves carbon performance in real factory environments. The findings aim to guide researchers and practitioners in transforming digital visibility into operational decisions that deliver measurable emission reductions, thereby deepening the understanding of how digital technologies contribute to sustainable manufacturing.

2. Materials and Methods

2.1. Sample and Study Area Description

This study includes 62 factories from electronics, machining, and chemical production. All factories operate regular weekday schedules and run continuous or semi-continuous production lines. Electricity is the main source of energy, and some sites also use natural gas for heating steps. The sample was chosen to cover different factory sizes, equipment types, and levels of digital monitoring. Each site had basic IoT sensors in place before data collection. These sensors recorded energy use, machine status, and operating hours under normal production conditions. No changes were made to production tasks during the sampling period, ensuring that all measurements reflect typical daily operation.

2.2. Experimental Design and Control Comparison

A before-after design was used to evaluate the effect of digital monitoring. The control period refers to factory operation without real-time monitoring, when measurements depended on manual checks and periodic meter readings. The experimental period refers to operation after IoT sensors, carbon dashboards, and scheduling tools were installed. Production plans, shift schedules, and work hours remained stable across both periods to minimize unrelated differences. This design allows a direct comparison between the two conditions and provides a clear basis for assessing changes in energy use and carbon emissions.

2.3. Measurement Methods and Quality Control

Energy use was measured with smart meters that had one-minute recording intervals. All meters were tested and verified before installation. Carbon emissions were calculated using local electricity emission factors. IoT sensors collected data on voltage, current, machine load, and runtime. Data were transmitted through secure wired networks to avoid signal loss. A 72-hour run-in period was applied to ensure stable operation before formal measurements. Daily checks were performed to identify missing records, abnormal peaks, and communication errors. Data affected by equipment faults or unexpected shutdowns were removed from the dataset to maintain consistency.

2.4. Data Processing and Model Formulation

Raw data were cleaned by removing faulty readings and aligning timestamps. Measurements were averaged into 15-minute intervals. Energy and carbon intensity were calculated for each main production step. A fixed-effects regression model was used to estimate the effect of digital monitoring. The model is written as:

$$Y_{it}=\alpha+\beta D_{it}+\gamma X_{it}+\mu_i+\varepsilon_{it}$$

where Y_{it} is energy use or carbon emissions for factory i at time t; D_{it} indicates whether digital monitoring was in place; X_{it} includes production load and working hours; and μ_i captures fixed site-specific factors.

To evaluate equipment-level savings, a simple performance index was used:

$$\text{Saving Rate}=\frac{E_{baseline}-E_{monitoring}}{E_{baseline}}$$

where $E_{baseline}$ and $E_{monitoring}$ represent energy use before and after monitoring.

3. Results and Discussion

3.1. Effects of Real-Time Monitoring on Energy Use

Real-time monitoring reduced energy waste by an average of 12% across the 62 factories (Figure 1). The reduction mainly came from identifying idle running, standby loss, and short load spikes that were previously unnoticed during manual inspections. Electronics plants reduced losses from HVAC and compressed air, while machining plants corrected abnormal spindle loads. Chemical plants improved heating and pump control through more consistent tracking. These changes were achieved without modifying production plans. Our findings are consistent with earlier work showing that visible machine-level energy data help operators respond faster to unusual consumption patterns [16]. For example, a study on an IoT-based monitoring system reported similar improvements after installing high-frequency energy meters in manufacturing lines. Unlike earlier case studies that focused on a single line, our results include multiple sectors and real factory schedules, giving broader evidence of the effect of continuous monitoring [17].

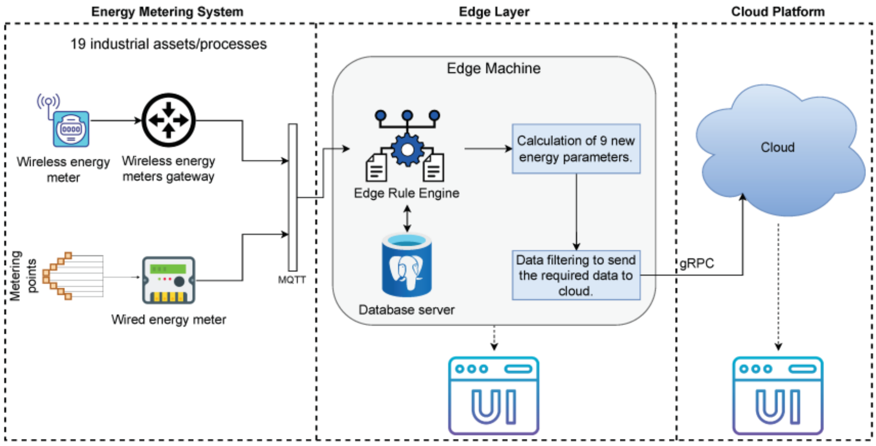

Figure 1. Diagram of the carbon-monitoring system with IoT sensors, data links, and the main dashboard.

3.2. Impact of Automated Scheduling on Emissions and Throughput

Automated scheduling produced an additional 9% reduction in emissions. The system shifted non-urgent tasks-such as curing, auxiliary pumping, and certain surface-treatment steps-to lower-carbon periods identified from grid intensity data. In machining plants, grouping high-load tasks helped reduce repeated start-stop cycles. Daily output was not affected. Previous studies using plant-level scheduling tools often showed strong prediction accuracy but provided limited evidence of actual production changes. A digital-twin-based scheduling study reported energy savings but did not link them to carbon outcomes [18]. Our results show that simple rule-based scheduling, combined with reliable carbon measurements, can reduce emissions across different manufacturing sectors without the need for complex optimization models.

3.3. Process-Level Carbon Mapping and High-Emission Processes

Process-level carbon maps revealed clear high-emission segments (Figure 2). Electronics plants showed high values in cleanroom HVAC and reflow ovens. Machining plants were dominated by compressed-air systems, spindles, and coolant pumps. Chemical plants showed high emissions in heating and solvent recovery. These maps helped factories identify where upgrades or process changes would have the greatest effect. Similar mapping ideas have been used in studies that analyze energy signatures in CNC systems for fault detection or efficiency improvement [19-21]. Our results extend this approach by attaching carbon factors to each process stage and linking them to production planning.

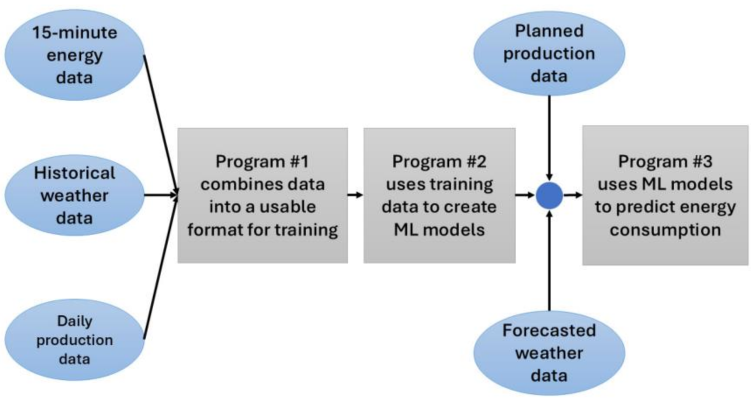

Figure 2. Carbon map showing the emission levels of key equipment groups across the production steps.

3.4. Comparison with Existing Research and Practical Implications

The combined 12% reduction from monitoring and 9% reduction from scheduling aligns with the range reported in recent studies on digital energy management in industrial systems. Previous research on IoT-based monitoring in buildings, logistics centers, and small factories also showed that simple feedback loops can lower electricity use [22-24]. Unlike those environments, however, manufacturing plants operate under strict safety and quality rules. Despite these constraints, all 62 factories maintained or improved throughput while reducing emissions, showing that the approach is suitable for real industrial conditions. Some limitations were observed. Several factories showed missing or unstable sensor data, which reduced the accuracy of carbon maps. Similar issues have been reported in studies on non-intrusive energy monitoring and industrial load prediction, where communication faults produced noisy signals. In addition, many factories still rely on monthly manual checks to confirm dashboard values, which slows response time. Future work may expand data coverage to include fuel-based processes, integrate scheduling tools with more advanced optimization methods, and test performance under carbon pricing or mandatory reporting rules.

4. Conclusion

This study evaluated how digital monitoring and automated scheduling can reduce carbon emissions in manufacturing plants. Data from 62 factories showed that real-time monitoring lowered energy waste by 12%, and simple scheduling rules produced an additional 9% reduction. These reductions were achieved without changing daily output. Process-level carbon maps helped locate the steps and equipment with the highest emissions, giving factories a clearer basis for improving their processes. The study provides practical evidence from real industrial environments and shows that digital tools can support emission reduction beyond small pilot trials. The results also suggest that these tools can be adopted in different industries with limited technical requirements. However, some limits remain. Several factories had unstable sensor data, and many still relied on manual checks to confirm dashboard values. The analysis also focused on electricity-related emissions and did not include fuel use or material-related carbon. Future work can extend the monitoring scope, test stronger scheduling methods, and examine the effect of policy measures such as carbon pricing on system performance.

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