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LinkedIn Revista Ingeniería de Construcción
ISSN: 0718-5073
Vol. 40
Special Issue 2025
DOI: https://doi.org/10.7764/RIC.00166.21

Real-time energy and CO_2 optimization in construction cranes through digital twins and lean construction

Optimización en tiempo real de energía y CO_2 en grúas de construcción mediante gemelos digitales y construcción lean

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Fecha de Recepción: 19/09/2025
Fecha de Aceptación: 14/10/2025
Fecha de Publicación: 22/12/2025
PAG: 1-13

Abstract

The construction sector is under growing pressure to reduce energy use and carbon emissions while sustaining operational efficiency. This study develops and validates an integrated framework for real-time optimization of crane energy performance by combining digital twin technology with Lean Construction principles. Three cranes—two tower cranes (C1, C2) and one mobile crane (MC) were monitored on a large construction site in Billund, Denmark, using IoT-enabled sensors over seven weeks, generating more than 16,000 ten-minute records. Key performance indicators (Idle Factor, Idle Time, and Night Baseload Index) were defined to capture non-productive energy use and linked to Lean concepts of waste elimination and continuous improvement. Results revealed that idle periods dominated crane energy profiles, with idle energy accounting for nearly 100% of C1's preparatory stage, 52% of C2's consumption, and 42% of MC's. Aggregated idle emissions totaled 126 $kgCO_2e$, representing approximately 55% of total crane-related emissions. By embedding predictive analytics and Lean-based KPIs into a digital twin platform, the framework delivers real-time visibility, automated alerts, and actionable insights for shutdown policies and task sequencing. This research provides one of the first approaches explicitly connecting digital twins and Lean Construction to reduce idle energy waste, advancing sustainable and data-driven site management.

Keywords: Digital Twin; Lean Construction; Crane; Idle Time; Energy Efficiency; CO_2 Emissions; Sustainable Construction.

Resumen

El sector de la construcción enfrenta una creciente presión para reducir el consumo energético y las emisiones de carbono, manteniendo al mismo tiempo la eficiencia operativa. Este estudio desarrolla y valida un marco integrado para optimizar en tiempo real el desempeño energético de grúas, combinando la tecnología de gemelos digitales con los principios de la Construcción Lean. Tres grúas, dos grúas torre (C1, C2) y una grúa móvil (MC) fueron monitoreadas en una gran obra en Billund, Dinamarca, mediante sensores habilitados con IoT durante siete semanas, generando más de 16.000 registros de diez minutos. Se definieron indicadores clave de desempeño (Factor de Inactividad, Tiempo de Inactividad e Índice de Carga Base Nocturna) para capturar el uso de energía no productiva y vincularlo con los conceptos Lean de eliminación de desperdicios y mejora continua. Los resultados revelaron que los periodos de inactividad dominaron los perfiles energéticos de las grúas, con energía ociosa representando casi el 100 % en la etapa preparatoria de C1, el 52 % del consumo de C2 y el 42 % de MC. Las emisiones ociosas agregadas totalizaron 126 $kgCO_2e$, equivalentes a aproximadamente el 55 % de las emisiones totales asociadas a las grúas. Al incorporar analítica predictiva e indicadores Lean en una plataforma de gemelo digital, el marco proporciona visibilidad en tiempo real, alertas automáticas y recomendaciones para políticas de apagado y secuenciación de tareas. Esta investigación presenta uno de los primeros enfoques que conecta explícitamente gemelos digitales y Construcción Lean para reducir el desperdicio energético por inactividad, avanzando hacia una gestión de obra sostenible y basada en datos.

Keywords: Construcción Lean; Gemelo Digital; Eficiencia Energética; Emisiones de CO_2; Grúas de Construcción; IoT.

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DOI: https://doi.org/10.7764/RIC.00166.21

1. Introduction

The construction sector is under increasing pressure to reduce environmental impact while maintaining productivity and safety (Patzlaff et al. 2014). Tower cranes play a central role in vertical construction projects by handling materials and coordinating site logistics, yet their continuous connection to power systems often results in substantial idle energy consumption. Studies estimate that idle periods can account for 30–40% of crane operating time, leading to wasted energy, unnecessary costs, and avoidable emissions (Hajjar and AbouRizk 2002; Motyčka et al. 2022).

At the same time, the industry is undergoing rapid digital transformation. Digital twins, defined as real-time virtual replicas of physical assets, connect sensor data, simulation, and decision-making (Yeung et al. 2025). Their application in construction has demonstrated potential for monitoring performance, predicting failures, and optimizing operations. Most research, however, has focused on mobile equipment such as excavators and trucks, leaving stationary yet energy-intensive assets like cranes underexplored (Hong et al. 2024; Zhong et al. 2023). Furthermore, the sustainability dimension of digital twins has often been limited to productivity and safety, without fully leveraging their potential to reduce energy waste and associated CO_2 emissions.

Recent studies have underscored the importance of linking energy performance monitoring with Lean and digital transformation strategies in construction. Teizer et al. (2020) emphasized that resource-efficiency tracking through IoT sensors enables substantial energy savings on jobsites. Likewise, Sacks et al. (2020) described how Digital Twin Information Systems can enhance operational visibility and sustainability through real-time data flows. From a Lean perspective, Sacks et al. (2010) highlighted that integrating digital tools with waste-elimination principles can substantially improve planning reliability and productivity. Together, these contributions justify the need for integrated frameworks capable of connecting energy monitoring, digital twins, and Lean Construction principles.

Lean Construction offers a complementary perspective. Rooted in waste elimination, continuous improvement, and flow optimization, Lean methods such as the Last Planner System (LPS) are widely used for production control (Ballard and Tommelein 2012). Yet their integration with equipment-level monitoring remains minimal. Idle energy use in cranes directly aligns with Lean's category of waiting waste. Embedding real-time insights into Lean routines can therefore provide a systematic pathway for efficiency gains and decarbonization.

This paper addresses these gaps by combining digital twins with Lean Construction to optimize crane operations in real time. Building on IoT-enabled monitoring of three cranes in a large project in Billund, Denmark, the study develops equipment-level performance indicators, including Idle Factor, Idle Time, and energy per lift cycle, and links them to Lean categories of waste. The proposed framework enables the visualization of inefficiency patterns and the translation of insights into actionable planning decisions such as task sequencing, idle shutdown policies, and continuous improvement routines.

2. Literature review

The construction sector faces increasing pressures to optimize operations, enhance efficiency, and reduce its environmental impact (Teizer et al., 2020). In this context, the use of digital twins has emerged as an innovative solution that enables the simulation, analysis, and optimization of physical assets based on real-time updated data. A digital twin is defined as an accurate virtual representation of a physical object, process, or system that is continuously updated through the integration of data from sensors, IoT devices, and other digital sources (Agostino et al., 2020). In the construction domain, a digital twin constitutes a virtual replica of a physical project component, such as a building, a machine, or a specific construction phase—linked to field-collected information, including BIM models, sensor data, drone imagery, and operational databases, to monitor, predict, and optimize construction progress in real time (Sacks et al., 2020). This technology not only enables a deeper understanding of physical system behavior but also supports informed decision-making oriented toward sustainability, safety, and productivity in complex environments.

In recent years, the use of digital twins for construction machinery and equipment has garnered growing attention due to their potential to enhance operational efficiency, reduce energy consumption, and optimize on-site decision-making. Research by Zhong et al. (2023) has shown that integrating digital models with real-time sensor data enables the monitoring of earthmoving equipment conditions, facilitating predictive maintenance and logistics planning. Similarly, Babazadeh et al. (2023) developed a method for generating construction site noise maps by combining BIM-derived noise source data with real-time IoT sensor measurements. The objective was to improve site planning and control noise

ISSN: 0718-5073
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DOI: https://doi.org/10.7764/RIC.00166.21

exposure, thereby protecting the health of workers and nearby communities. These studies lay the foundation for applying digital twins not only to mobile vehicles but also to highly critical stationary machinery, such as tower cranes.

From the perspective of Lean Construction, these technologies represent a fundamental tool for waste reduction, workflow improvement, and value creation for clients. In particular, the real-time monitoring of cranes through digital twins makes it possible to identify and eliminate non-value-adding activities, such as non-productive energy consumption (Salgin et al. 2016). In this framework, waste refers to any resource use that does not directly contribute to the value of the final product, including waiting times, unnecessary idle periods, redundant movements, and unjustified energy use. Idle time in cranes is recognized as a specific category of operational waste within the Lean system. This classification makes it possible to align crane energy monitoring with Lean Construction principles such as operational visibility, variability reduction, and continuous improvement, thereby supporting data-driven decisions and context-specific optimization strategies.

One of the most important assets in vertical construction projects is the tower crane, given its central role in lifting and transporting heavy materials at height. These machines largely determine the pace of project progress, influence site logistics, and represent a significant source of energy consumption (Motyčka et al. 2022). Despite their operational importance, crane usage is often suboptimal, resulting in high idle times, excessive energy consumption, and material supply chain bottlenecks. Their proper operation significantly influences project performance, safety, and energy consumption (Shapira & Ben-David, 2017). However, research has shown that cranes in construction projects experience considerable idle time, which negatively affects both operational efficiency and the project's environmental sustainability (Sacks et al., 2010).

Studies such as Hajjar and AbouRizk (2002) have found that crane idle time can account for up to 40% of total operating time, associated with deficiencies in coordination, material waiting, or delayed operational decisions. This problem is exacerbated by the lack of real-time visibility into effective equipment use, which limits the effectiveness of corrective interventions. With the advancement of digital construction, monitoring solutions based on IoT sensors and tracking systems have emerged, enabling the recording of key operational variables, such as energy consumption, work cycles, and downtime events. Recent literature has addressed the use of monitoring technologies in equipment such as excavators (Zankoul et al. 2015) and backhoes (Hong et al. 2024). However, studies focused exclusively on cranes remain limited, despite their operational relevance.

3. Research gaps and objectives

Despite the growing application of digital twins in construction, most studies have concentrated on mobile equipment such as excavators and trucks. Tower cranes, which are energy-intensive and central to site logistics, have received little attention. Existing work has also emphasized productivity, safety, or predictive maintenance, without fully addressing the potential of digital twins to quantify and reduce idle energy use and related CO_2 emissions.

Similarly, Lean Construction has been widely applied to production planning and waste reduction at the process level, but its integration with equipment-level monitoring remains minimal. This gap limits the connection between real-time energy insights and Lean-based decision-making.

This study addresses these gaps by combining IoT-enabled digital twins with Lean Construction principles to monitor, analyze, and optimize crane operations in real time. Using data from three cranes on a large construction project in Billund, Denmark, the research objectives are to (1) reveal energy inefficiency patterns in crane operations through digital twin monitoring, (2) establish equipment-centric Lean KPIs that link crane performance to waste categories, and (3) validate the framework's potential to reduce idle energy consumption and CO_2 emissions through predictive analytics and Lean-informed strategies.

4. Methodology

This study employs a case study approach on a large-scale construction project in Billund, Denmark. Three cranes were monitored: two stationary tower cranes (C1 and C2) and one mobile crane (MC) (Table 1). These machines were selected because of their central role in vertical construction operations and their contribution to the site's overall energy load. Electrical consumption was monitored using Acembee Bee v1.8 industrial three-phase energy sensors equipped with JSY-MK-333 embedded metering modules. The sensors were installed on the main power feed of each crane, capturing all electricity consumption events, including lifting, slewing, auxiliary systems, and standby.

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Data collection spanned approximately 50 days per crane, covering seven weeks in April–May 2025. Each crane recorded between 5,200 and 5,500 valid 10-minute intervals, producing over 16,000 observations in total.

Table 1. Crane specifications.

Id	Type	Model	Manufacturer
C1	Tower Crane	125k	Liebherr
C2	Tower Crane	125k	Liebherr
Mc	Mobile Crane	M21-4wds	Montalift

4.1 Digital Twin Design

The monitoring system was structured as a digital twin architecture with four layers.

1. Sensing layer: Clamp-on current transformers and digital meters captured real-time active power, current, and voltage.
2. Communication layer: Data were transmitted via the MQTT protocol to a Python-based edge client for preprocessing and packaging.
3. Storage layer: A time-series database (InfluxDB) stores all readings with timestamps and crane identifiers, enabling flexible integration with dashboards, BIM models, or Lean planning tools.
4. Visualization layer: For this study, a dedicated web solution was under development, while the exported data were analyzed statistically.

4.2 Data preprocessing

Raw data consisted of cumulative energy readings at irregular timestamps. Several steps were applied to structure the dataset for analysis.

1. Resampling: Measurements were resampled into a uniform 10-minute grid between the first and last valid timestamp.
2. Imputation: Missing rows were explicitly inserted with zero consumption, ensuring inactive periods were represented.
3. Conversion: Timestamps were standardized to local time (Europe/Copenhagen).
4. Cleaning: Outliers and spurious values were filtered using statistical thresholds.
5. Segmentation: Each record was classified into daytime (06:00–18:00) or nighttime (18:00–06:00) categories, allowing analysis of operational vs. non-operational hours.

4.3 Idle Detection Method

To distinguish idle from active states, a statistical threshold was derived from nighttime consumption profiles, assumed to reflect standby conditions. The threshold was defined as (see Equation 1):

$$P_{\text{idle\_max}} = m_{\text{night}} + 3 \cdot MAD_{\text{night}} \quad \textbf{\textit{(1)}}$$

MAD denotes the Median Absolute Deviation. This conservative bound captured normal baseline fluctuations while excluding operational spikes. The use of MAD for threshold definition was selected due to its robustness against outliers and its suitability for non-Gaussian energy distributions typical of on-site sensors. This statistical approach minimizes the risk of misclassifying short power fluctuations as operational activity and has been successfully applied in similar energy-profiling contexts (e.g., industrial standby detection and equipment-load analysis). If insufficient nighttime samples were available, the method was applied to the full dataset; if still scarce, the 75th percentile of power demand was used as a fallback. Each 10-minute interval was then classified as idle or active depending on whether its average power consumption exceeded the threshold.

4.4 KPI definition

Three indicators were computed to translate raw sensor data into actionable insights (Table 2).

1. Idle Factor (IF): Share of total energy consumed during idle states (Equation 2).
2. Idle Time (IT): Share of monitored intervals classified as idle, regardless of energy consumed (Equation 3).
3. Night Baseload Index (NBI): Proportion of total energy consumed during nighttime hours (Equation 4).

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This dual perspective (energy-based and time-based) captures both the intensity and duration of non-productive operation. These indicators were linked to Lean Construction principles, with IF representing waiting waste, IT representing reinforcing visibility of idle periods, and NBI capturing unnecessary energy use, thereby creating a direct bridge between digital monitoring and Lean waste categories.

Table 2. Key Performance Indicators (KPIs) with formulas.

KPI	Formula	Description
IF	$IF = \frac{E_{\text{idle}}}{E_{\text{tot}}} \times 100(\%)$ (2)	The fraction of total energy consumption that occurs during idle states.
IT	$IT = \frac{N_{\text{idle}}}{N_{\text{tot}}} \times 100(\%)$ (3)	The fraction of total monitored 10-minute intervals classified as idle.
NBI	$NBI = \frac{E_{\text{night}}}{E_{\text{tot}}} \times 100(\%)$ (4)	The proportion of total energy consumed during nighttime periods

4.5 Energy and CO_2 quantification

Energy consumption (kWh) was separated into idle and active components for each crane and for day/night periods. Environmental impact was quantified by applying an average Danish grid factor of 0.175 $kgCO_2e/kWh$. This consistent approach enables comparison across cranes while leaving room for future sensitivity analyses based on dual grid factors.

4.6 Data analysis methods

Descriptive statistics and time-series analyses were applied to examine hourly, daily, and weekly consumption patterns. Comparative benchmarking between the tower and mobile cranes was conducted to highlight efficiency differences related to equipment type and operational scheduling. A correlation analysis between IF and Idle Time IT was performed to verify the consistency between energy- and time-based indicators. Temporal aggregation was used to identify recurrent idle peaks, while visual analytics supported the detection of non-productive nighttime loads. The analysis outcomes were subsequently linked to Lean-based performance evaluation, enabling interpretation of results within waste-reduction categories such as waiting and over-processing.

5. Results and discussion

5.1 Energy Partitioning

Energy consumption was divided into idle and active components for each crane (Table 3).

Table 3. Total energy partitioning (kWh) by crane, showing idle and active energy consumption and Idle Factor (IF).

Crane	Total Energy [kWh]	Idle Energy [kWh]	Active Energy [kWh]	Idle Factor [%]
C1	385.29	384.78	0.51	99.9
C2	580.53	304.16	276.37	52.4
MC	72.09	30.23	41.86	41.9

C1 operated almost exclusively in idle mode (≈100%). This outcome was expected, since C1 was in its preparation and installation stage during the monitoring period and did not perform productive lifting work. Therefore, the nearly complete idle profile aligns with its project role at that time. C2 displayed a more balanced profile, with significant active energy during the day; however, given that the observations correspond to the

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initial construction phases, the crane was not yet required at full capacity, which explains its relatively low occupancy. MC showed 42% idle share, with meaningful operational activity (see Figure 1).

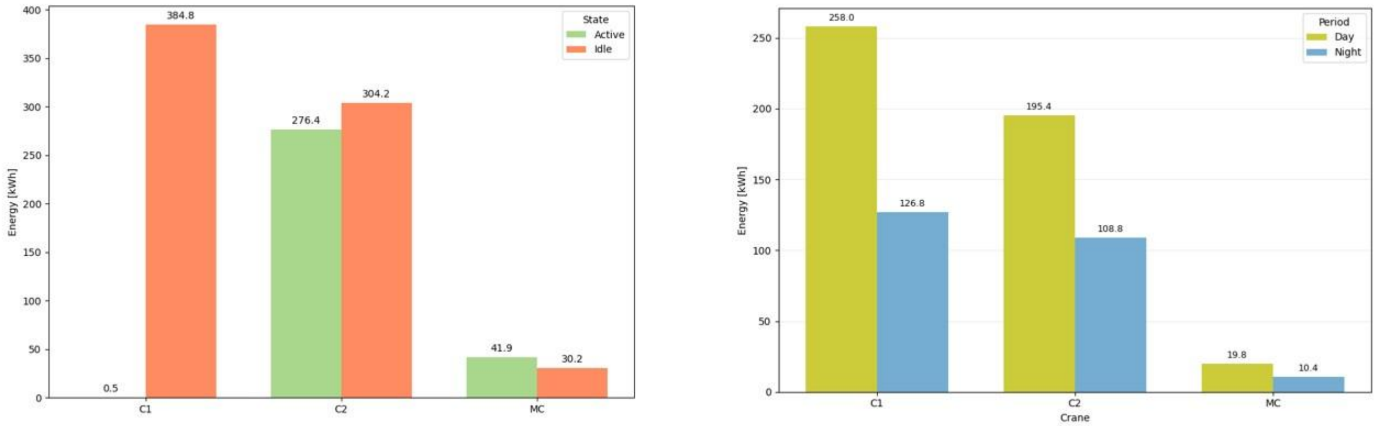

Figure 1. Idle and active energy per crane: (a) Total idle and active energy per crane, (b) Total idle energy per crane, day and night.

5.2 Day vs. Night comparison

The day/night split highlights patterns of non-productive nighttime consumption (see Figure 2).

Table 4. Day and night energy distribution across cranes and corresponding Idle Factors.

Crane	Day Energy [kWh]	Day Idle [kWh]	Day Active [kWh]	IF Day [%]	Night Energy [kWh]	Night Idle [kWh]	Night Active [kWh]	IF Night [%]
C1	258.52	258.01	0.51	99.8	126.77	126.77	0.00	100.0
C2	439.13	195.40	243.73	44.5	141.40	108.76	32.64	76.9
MC	56.64	19.80	36.84	35.0	15.45	10.43	5.02	67.5

Nighttime idle loads are particularly significant for C2 and MC, while C1 remained idle both day and night (Table 4). It is important to note that subsequent observations from site workers revealed that some cranes were intentionally left powered during the night to prevent equipment damage from freezing (Figure 3). This practice explains the minimal but consistent nighttime consumption recorded in the dataset

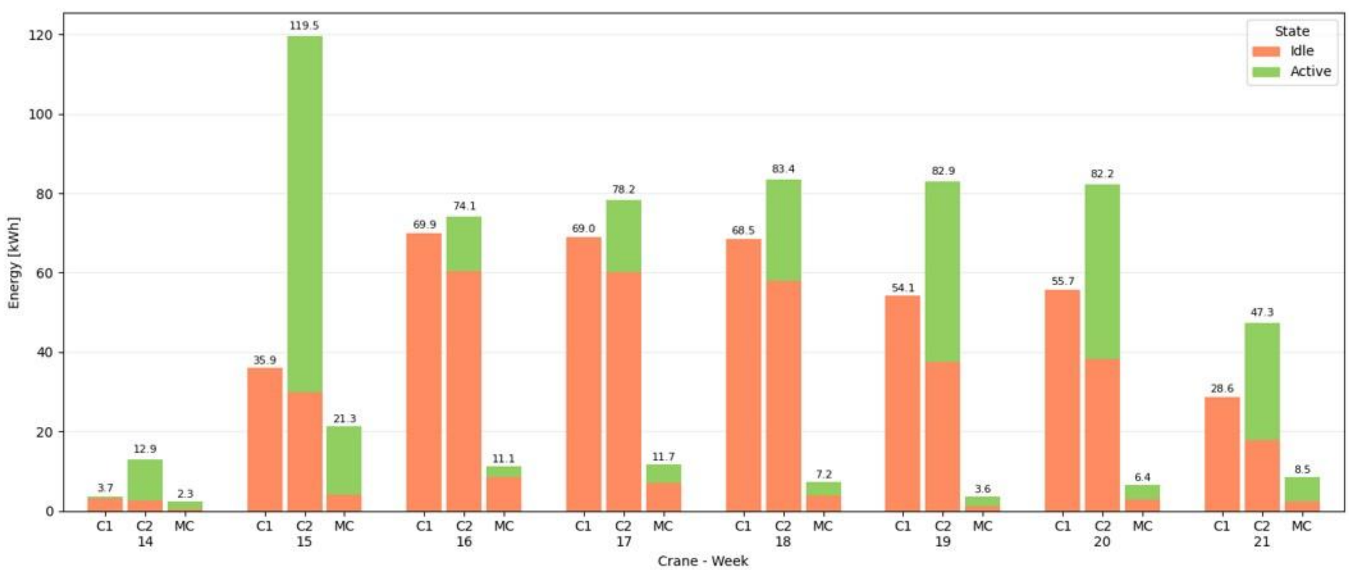

Figure 2. Weekly idle and active energy consumption per crane.

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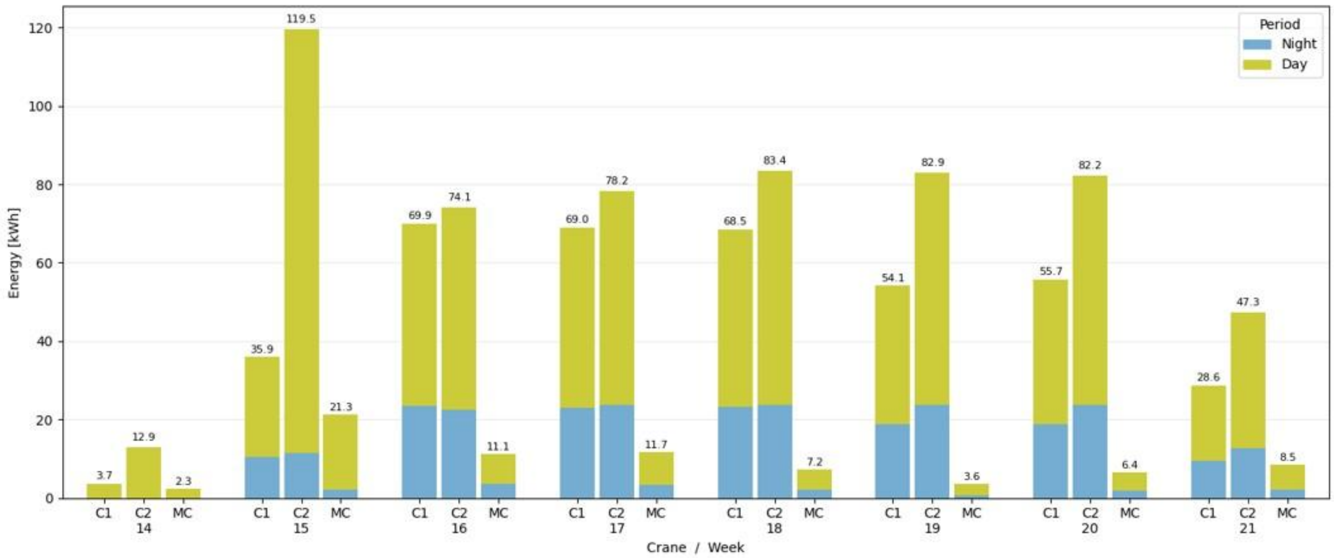

Figure 3. Weekly idle energy per crane, comparing day and night periods.

5.3 Idle Time Analysis

Idle Time (IT) results show the proportion of time each crane remained in a non-productive state (Table 5).

Table 5. Idle Time (IT) results as a percentage of monitored intervals, disaggregated into day and night periods.

Crane	IT Total (%)	IT Day (%)	IT Night (%)
C1	99.9	99.8	100.0
C2	80.4	76.5	88.6
MC	84.4	82.8	87.7

C1 remained virtually idle throughout, with both Idle Factor (≈100%) and Idle Time confirming standby-only operation. C2 showed ~80% Idle Time, higher than its 52.4% Idle Factor, reflecting frequent idle intervals but lower idle energy due to daytime activity. MC also displayed high Idle Time (~84%) versus a lower Idle Factor (41.9%), underscoring the need to analyze both indicators since active phases consumed proportionally more energy (Figure 4).

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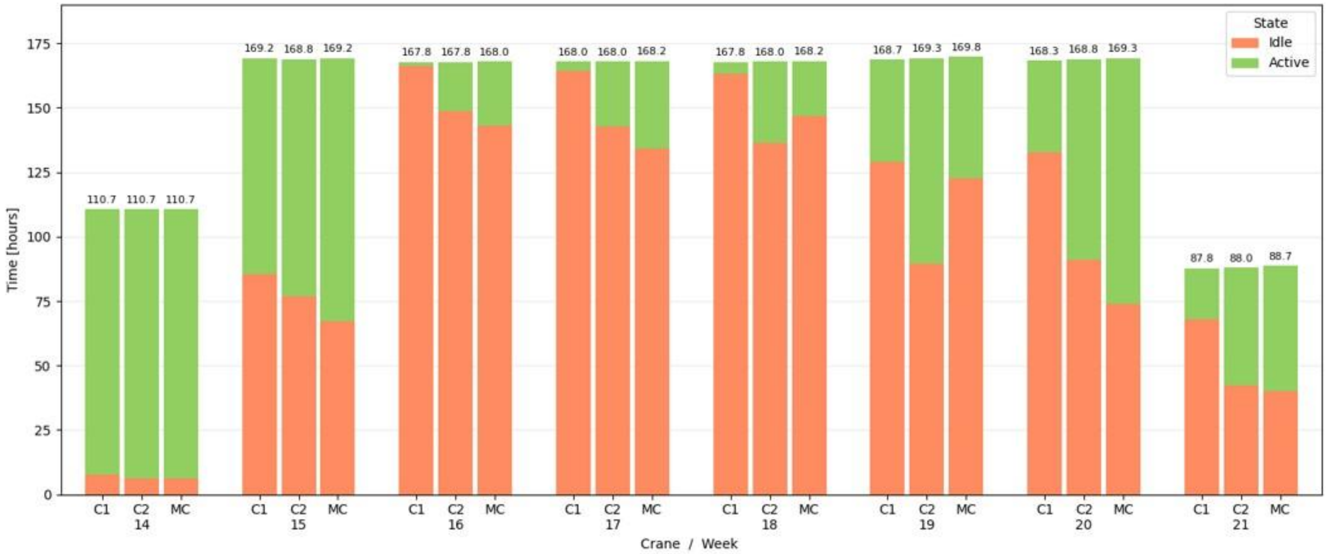

Figure 4. Weekly stacked idle and active time (Idle Time vs. Active Time) per crane.

The observed idle factors are consistent with those reported in previous investigations. (Motyčka et al. 2022) documented similar idle proportions in tower cranes under partial-load operation, while Shapira and Ben-David (2017) highlighted the strong dependency of energy efficiency on task sequencing and coordination. Comparable idle-time ranges (40–80 %) have also been reported for heavy equipment such as excavators and backhoes (Hong et al. 2024; Zankoul et al. 2015). These parallels indicate that the high idle energy shares identified in this study are representative of early-phase site operations rather than exceptional outliers, reinforcing the need for data-driven monitoring and Lean-informed management interventions.

5.4 CO_2 Emissions

Using a factor of 0.175 $kgCO_2e/kWh$, idle and active energy were converted into emissions (Table 6).

Table 6. Idle and active CO_2 emissions ($kgCO_2e$) per crane, including total emissions.

Crane	Idle Emissions ($kgCO_2e$)	Active Emissions ($kgCO_2e$)	Total ($kgCO_2e$)
C1	67.33	0.09	67.42
C2	53.23	48.37	101.60
MC	5.30	7.32	12.62

C1's emissions stem almost entirely from idle energy, reflecting its preparatory status and the absence of productive operation. C2 shows a balanced split between idle and active emissions, with approximately half of its emissions arising from non-productive consumption. The total emissions of around 102 $kgCO_2e$ are consistent with observations reported for comparable cranes operating under low-capacity requirements during early construction phases (Figure 5).

MC has lower absolute emissions overall but still exhibits a large idle contribution relative to its limited productive activity.

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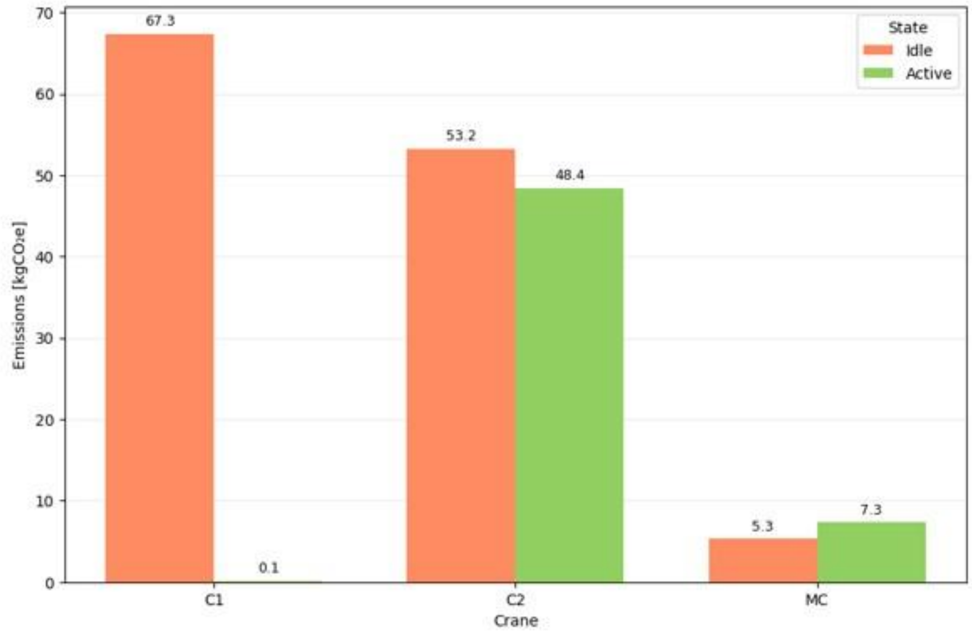

Figure 5. Idle vs. active CO_2 emissions per crane.

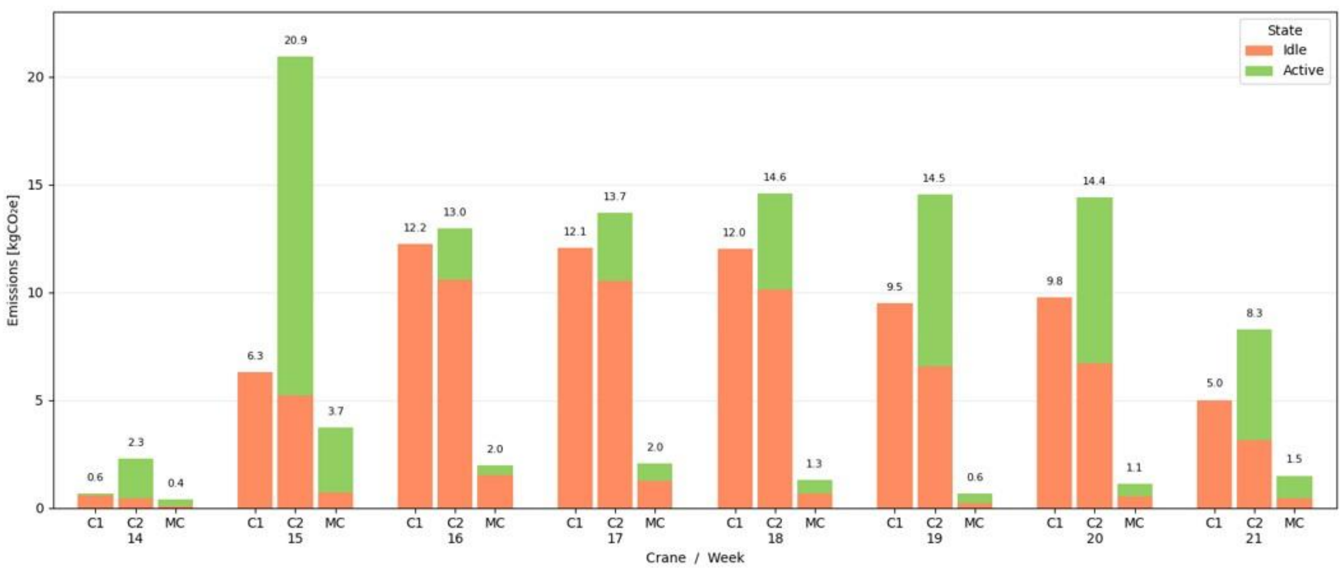

Figure 6. Weekly stacked idle vs. active CO_2 emissions per crane.

When aggregating across all three cranes, idle emissions amounted to approximately 126 $kgCO_2e$ (about 55% of the total), while active emissions reached 56 $kgCO_2e$. This distribution indicates that the majority of emissions are attributable to idle periods. Such a pattern highlights the critical need to review and optimize site practices and crane-related activities in order to mitigate this waste and achieve meaningful reductions in carbon impact (Figure 6).

Although the case study was conducted in Denmark, the proposed framework can be readily adapted to other national contexts. In regions with higher grid-emission factors, the potential carbon savings from idle-energy reduction would be even greater. Likewise, in countries with limited access to automated metering infrastructure, low-cost IoT sensors and open-source analytics can provide an affordable pathway to implement similar systems. The combination of digital-twin monitoring and Lean performance indicators thus offers a transferable methodology for promoting energy-aware and sustainable site management globally.

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6. Limitations and future research

The monitoring period coincided with early construction phases characterized by low-demand activities such as site preparation. As a result, total emissions were relatively modest, and one crane (C1) was powered primarily for installation and testing. While this reflects the actual energy profile of preparatory stages, it limits comparability with more intensive phases of crane operation. At the same time, the results provide a useful insight into the emissions associated with crane setup and commissioning, an area rarely addressed in the literature.

Another limitation concerns the energy conversion method. The study applied an average Danish grid factor of 0.175 $kgCO_2e/kWh$, which provides consistency but does not capture real-time fluctuations in grid composition. Incorporating dynamic emission factors, as published by Danish energy authorities, would enable a more realistic assessment of environmental impact.

A further limitation is the use of 10-minute intervals. While adequate for energy partitioning, this resolution does not allow the direct identification of detailed activity cycles. Shorter intervals could improve the accuracy of distinguishing between lifting operations, standby, and auxiliary functions.

Future research should extend monitoring to later construction phases, where higher lifting demand is expected, and compare emission patterns across project stages. Another promising direction is to connect energy monitoring with the actual activities performed by cranes and other machinery. Linking operational data with machine learning techniques could enable the prediction of future energy consumption under specific circumstances, providing a basis for proactive planning and optimization. Expanding the framework to cover other energy-intensive machines would further enhance its applicability to site-wide optimization and carbon reduction strategies.

7. Conclusions

The analysis confirmed that cranes in preparation and maintenance stages exhibit very high idle shares. For C1, which was powered mainly for installation and testing, idle operation reached almost 100%, with corresponding emissions of approximately 67 $kgCO_2e$. This reflects the expected profile of cranes not yet engaged in productive lifting but also highlights the relevance of accounting for emissions linked to preparatory phases.

C2 demonstrated a more balanced profile, with 52% of its energy consumed during idle states and 80% of intervals classified as idle. Although consistent with ranges reported for comparable cranes, these figures remain at the higher end of the spectrum and point to significant inefficiencies. The mobile crane (MC) showed 42% idle energy and 84% idle time, indicating that, despite lower overall consumption, idle prevalence is still substantial. When compared with C2, the mobile crane recorded lower absolute emissions, suggesting that mobile cranes may represent a more efficient choice for site preparation activities.

Day and night analysis further revealed non-productive nighttime consumption. In some cases, cranes were intentionally left powered overnight, leading to unnecessary idle loads. This finding prompted corrective actions by site managers, demonstrating the value of real-time monitoring for operational decision-making.

Overall, the results confirm that integrating digital twin monitoring with Lean-based indicators provides managers with a practical tool to identify waste, assess idle operation, and support energy-conscious planning decisions. Extending such approaches across construction sites could enhance both operational efficiency and carbon reduction outcomes.

8. Use of Artificial Intelligence

AI–based tools were employed solely to support language refinement and clarity improvement during manuscript preparation. Specifically, Grammarly was used for grammar checking, stylistic editing, and paraphrasing to ensure academic writing quality and consistency. No generative AI tools were used for content creation, data analysis, or interpretation of research results.

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DOI: https://doi.org/10.7764/RIC.00166.21

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