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Time Carbon Footprint Accounting In Hybrid Machining Lines

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Abstract

Hybrid manufacturing lines—particularly those integrating laser cladding, precision milling, and automated inspection—present complex and interdependent flows of energy, materials, and emissions. These flows are typically non-linear and vary widely with process parameters such as re-clad depth, machine state transitions, and energy source fluctuations. To quantify and analyze these real-time variabilities, we present a novel integration of line-side programmable logic controller (PLC) data with internationally recognized emission benchmarks, specifically ISO 14067 standards for product carbon footprinting.

Our approach enables high-resolution, second-level carbon footprint dashboards that reflect the instantaneous environmental impact of each machining operation. These dashboards fuse process-specific energy metrics (e.g., spindle power, gas flow, thermal cycles) with dynamic emission factors, allowing for transparent and time-synchronized carbon tracking throughout the production lifecycle.

A pilot deployment on a turbine blade remanufacturing cell revealed significant insights: the carbon footprint per part exhibited a variance of ±12%, primarily driven by differences in re-cladding volume and energy consumed during post-processing. Such fine-grained carbon accounting not only enhances environmental transparency but also enables data-driven decisions in procurement and supplier evaluation. Specifically, the variability *captured in per-part emissions provides a robust foundation for implementing dynamic eco-supplier rating systems, where vendors can be ranked and rewarded based on verified real-time sustainability performance.*

This framework demonstrates how hybrid manufacturing environments can transition from static environmental reporting to live, actionable insights that drive greener and more accountable production strategies.

Keywords: *Carbon footprint; Hybrid machining; PLC integration; Sustainability dashboard; Turbine repair*

INTRODUCTION

Hybrid machining lines—cellular systems that combine subtractive and additive processes in a single production flow— promise shorter lead times and greater design freedom. Yet they knit together lasers, milling spindles, motion stages, dryers and post processing booths that draw power from varied sources at uneven duty cycles. Until recently, most environmental assessments looked only at average electricity use per part. Real time carbon footprint accounting brings finer insight: it couples second by second power readings, shop floor sensor data and cloud based emission factors to show how every tool path, spindle pause or purge cycle affects greenhouse gas output. The following paper presents a structured view of real time accounting in hybrid lines, outlines a low latency data architecture, and reports test bench results from a mid volume aerospace nozzle cell.

LITERATURE REVIEW

Early carbon tracking studies in machining focused on high speed milling centres; Addington and Seo (2014) showed that idle states contributed up to 40 % of life cycle emissions. Later, Huerta et al. (2018) extended time resolved monitoring to selective laser melting units, but their work treated additive and subtractive steps in isolation. Integrated line level models emerged only when Pirim and Lochin (2021) combined OPC UA machine data with ISO 14064 inventories, though they still relied on hourly energy tariffs. Recent digital shadow architectures (Wei et al., 2023) push granularity down to 100 ms, enabling near real time eco feedback to the machine controller. Research gaps persist: (a) machine learning estimators for thermal energy flows inside powder chambers, (b) dynamic allocation of renewable heavy power blocks, and (c) standardised uncertainty budgets for sensor derived emission factors.

HYBRID MACHINING LINE OVERVIEW

A typical hybrid line for titanium turbine parts involves (1) laser powder bed fusion (LPBF) deposition, (2) in situ laser assisted milling, (3) stress relief heat treatment, (4) five axis finishing, and (5) automated visual inspection. Material flow is cyclic; fixtures travel on AGVs between modules while remaining clamped to a common Z frame to retain datum integrity. Power demand oscillates sharply—peaking during laser shots (up to 3 kW) and falling to < 200 W during AGV moves. Compressed air, argon shielding and chilled water loops add Scope 2 and Scope 3 loads that conventional part average metrics mask.

Table 1 — Principal emission sources in a hybrid Ti 6Al 4V nozzle line

Direct (Scope 1)	Shield-gas leakage, propane furnace burners
Indirect (Scope 2)	Grid electricity for lasers, spindles, drives, chillers
Up-stream (Scope 3)	Powder atomisation energy, cutting-fluid production, tool-steel inserts

METHODOLOGY FOR REAL TIME CARBON ACCOUNTING

The proposed framework links edge devices, a message broker and a cloud analytics layer:

1. **Sensor portfolio –** Clamp on Rogowski coils measure phase currents of each axis drive and laser PSU at 1 kHz. PT100 probes on chiller loops capture latent heat removal, while flowmeters log argon litres per minute.

2. **Event binding –** MTConnect adapters stamp every NC block with a universal timestamp, allowing synchronous blending of power and machine state data.

3. **Emission factor engine –** Grid CO_2 intensity values arrive via an API from the regional load dispatch centre at five minute cadence; propane and argon factors follow IPCC tier 1 tables.

4. **Carbon ledger** – A Kafka broker streams fused tuples (timestamp, kWh, kg CO_2e) to a time series database (InfluxDB). The ledger accrues marginal emissions per equipment class and tags them to the active part ID.

5. **Feedback loop** – Every 60 s a lightweight MQTT message relays cumulative emissions to the cell PLC. If the current part exceeds its target envelope, the PLC staggers non critical spindle warm up to a later wind generation window.

Table 2 — Recommended data streams and sampling intervals

Data type	**Sensor / source**	**Interval**	**Typical accuracy**
Electrical power	Rogowski coil + 24-bit ADC	1 kHz	± 1.2 %
Shield-gas flow	Thermal mass flow sensor	10 Hz	± 1.5 %
Machine state	MTConnect adapter	Event-driven	ISO 14649 exact
Grid CO_2 factor	Utility REST API	5 min	± 3 % (regional)
Furnace load	PLC analog input	2 Hz	± 2.0 %

DATA ARCHITECTURE AND SENSOR INTEGRATION

At the lowest tier, each machine module is equipped with a fan less edge node built around a Raspberry Pi Compute Module 4 (2 × Cortex A72, 4 GB RAM). The board boots an RT Linux 6.6 rt kernel that reserves one core exclusively for deterministic tasks, leaving the second core to housekeeping and secure networking. GPIO/CSI lanes interface to an on board Texas Instruments C2000 digital signal processor (DSP) that receives simultaneous sampling, 24 bit ADC data from Rogowski coil interfaces, thermal mass flow sensors, and Pt100 ratiometric bridges.

The DSP executes a cascaded IIR anti alias filter followed by an incremental trapezoidal integrator over 50 ms sliding windows—long enough to average out PWM noise yet short enough to capture sub second laser duty bursts. Filter coefficients are flashed at commissioning and can be hot patched over CAN FD if recalibration is required. Resulting tuples 〈timestamp, power_W, sensor_ID〉 are DMA copied into a double buffer in shared RAM; once a buffer fills, the real time core publishes it via a ZeroMQ IPC channel while the

DSP starts filling the alternate buffer, ensuring zero gap acquisition even under worst case GC pauses.

For field to broker messaging the Pi runs nats jetstream inside a rootless Podman container. Each payload is wrapped in Protocol Buffers, signed with an ECDSA 256 key stored in the node's TPM 2.0, and encrypted in flight with mutual TLS 1.3. Certificate enrolment follows an ACME flow against an internal PKI; short 30 day validity windows and automatic rotation mitigate credential sprawl. Firewall rules expose only ports 4222 (NATS) and 123 (PTPv2) to the shop VLAN, limiting the attack surface.

Sub microsecond correlation between sensor bursts and NC block events is achieved through Precision Time Protocol v2 end to end transparent clock mode. A grand master IEEE 1588 clock disciplines both CNC and edge nodes; observed worst case skew after eight hours of free run is < 400 ns, tight enough to align 6 kHz spindle current spikes with G code timestamps for tool wear analytics.

In the cloud ingestion layer, a Kafka Connect cluster pulls JetStream subjects in real time and writes ORC encoded micro batches to an S3 compatible object store. A separate Spark Structured Streaming job converts raw packets to a columnar Parquet lakehouse partitioned by {site_id, yyyy mm}. LZ4 HC compression averages 6:1 on integer dense power traces, allowing a full year of 1 kHz data for ten hybrid cells to sit comfortably in ≈ 2 TB. Schema evolution is handled with Apache Iceberg, so new sensor fields (e.g., hydrogen flow) can be added without back migration.

Finally, Grafana dashboards and Python notebooks access a governed view layer exposed via Trino SQL. Engineers obtain < 200 ms query latency for two day windows, enabling live energy per part scorecards, while data scientists mine the same lake for long horizon carbon intensity trends feeding scheduling algorithms. Nightly object lock backups to an off site bucket satisfy ISO 27001 disaster recovery requirements, completing a resilient, secure, and extensible data stack for real time carbon analytics in hybrid machining lines.

CHALLENGES

Sensor drift. Heat near laser cabins skews Hall effect coils; quarterly calibration is mandatory.

Data privacy barriers. Machine tool builders may encrypt internal signals, forcing indirect inference—e.g., deducing laser duty from enclosure door time.

Emission factor volatility. Indian grid intensity swings from 150 g CO_2e / kWh at night to > 800 g CO_2e during coal peak hours, injecting uncertainty into per part metrics.

Economic alignment. Operators sometimes override eco limits to meet takt time when penalty costs are low.

Legacy assets. Older CNCs lack native adapters, so retrofit costs (≈ □ 55 000 per spindle) may deter adoption.

SCOPE

The real time ledger covers gate to gate boundaries: from powder hopper loading to boxed, inspected part. It excludes upstream alloy smelting and downstream customer transport. The methodology suits:

- Mid volume aerospace and medical lines (10–500 parts /month).
- Hybrid cells that mix LPBF + CNC or DED + grinding.
- Grid regions where renewable share varies hourly, making dynamic scheduling fruitful.

Excluded are manual workstations without PLC hooks and batch furnaces lacking continuous sensors.

RESULTS AND DISCUSSION

A five day pilot ran on a three module line at BrightForge Technical Institute, Himachal Pradesh. Two nozzle batches (A and B) were machined: batch B employed eco feedback, batch A served as baseline.

Table 3 — Carbon outcomes for two nozzle batches (per part)

Metric	Baseline A	Eco-feedback B	Reduction
Electrical energy (kWh)	28.5	24.1	15.4 %
Shield-gas use (L)	112	105	6.3 %
Total CO_2 e (kg)	21.7	16.9	22.1 %

Metric	Baseline A	Eco-feedback B	Reduction
Cycle time (min)	97	100	+3.1 %

The ledger pinpointed two high impact events: (1) laser power up surges of 1.2 kWh that lasted barely 90 s but cost 600 g CO_2e at coal peak; (2) spindle idle intervals during AGV travel that wasted 2.4 kWh per part. Simple control tweaks—delaying laser warm up to 22:30 IST and commanding spindle sleep during trips—delivered most gains. Operators initially distrusted carbon alarms; a traffic light HMI (green < target, yellow ± 5 %, red > 5 %) improved acceptance.

FUTURE RESEARCH DIRECTIONS

Predictive eco scheduling that fuses weather based solar forecasts with order books could pre stage high energy steps when renewables dominate the grid. Digital twins enriched with thermal CFD may estimate hidden furnace losses in real time, closing Scope 1 gaps. Finally, cross factory blockchains might exchange anonymised part level footprints, letting OEMs rank suppliers by verified carbon intensity and nudging the entire value chain toward net zero trajectories.

CONCLUSION

Real-time carbon footprint metrics provide a transformative shift in how hybrid machining lines are operated and managed. By enabling instantaneous feedback on energy consumption and greenhouse gas emissions, operators are no longer dependent on delayed sustainability reports or quarterly environmental audits. Instead, they gain the ability to make informed, eco-conscious decisions during the actual machining process—whether that means adjusting laser dwell times, pausing non-essential systems during high-emission periods, or rescheduling high-load operations to align with cleaner energy availability.

This continuous visibility not only fosters a culture of accountability on the shop floor but also opens new avenues for closed-loop optimization in production planning. Integrating the social cost of carbon into scheduling algorithms further elevates this approach. By assigning a real-world economic value to emissions generated per part or per operation, manufacturing systems can prioritize jobs based on both profitability and environmental responsibility. For example, a high-emission part might be deferred until renewable grid intensity improves, or a low-emission task may be expedited to meet both production and ESG (Environmental, Social, and Governance) targets.

Overall, embedding carbon intelligence directly into the operational core of hybrid machining systems represents a significant step toward greener, smarter, and more responsive manufacturing ecosystems.

REFERENCES

- Kapoor, R., & Srinivasan, M. (2022). Real-time monitoring systems in hybrid manufacturing lines: Challenges and solutions. Journal of Smart Machining Systems and Applications, 9(3), 145–158.
- Verma, A., & Iyer, T. (2021). Carbon footprint estimation models for additive-subtractive hybrid machining. Indian Journal of Advanced Manufacturing Technology, 5(2), 76–85. Deshmukh, N., & Patel, S. (2020). Integration of IoT sensors for energy analytics in CNC and laser-based processes. International Journal of Emerging Mechanical Engineering, 11(1), 21–34. https://ijeme.org/articles/iot-energy-cnc
- Pirim, M., & Lochin, T. (2021). Cloud-integrated carbon tracking for digital manufacturing. International Journal of Sustainable Production Systems, 18(4), 298–312. https://doi.org/10.1016/j.ijsps.2021.03.012
- Huerta, J. M., & Bergstrom, E. (2018). Time-resolved carbon accounting in additive manufacturing environments. Procedia CIRP, 69, 230–235.
- Sharma, V., & Reddy, B. S. (2023). Sensor fusion techniques for hybrid machining energy profiling. Indian Journal of Industrial Automation, 7(1), 55–68.
- Wei, Y., Chen, L., & Nakamura, H. (2023). Digital shadow architectures for real-time sustainability assessment in manufacturing lines. Journal of Advanced Manufacturing Informatics, 16(2), 101–115.
- Banerjee, D., & Krishnamurthy, R. (2022). Development of low-cost carbon footprint monitoring systems in Indian MSME sectors. Journal of Indian Smart Manufacturing Research, 6(4), 119–131. https://www.jisrm.in/articles/monitoring-msme
- Addington, S., & Seo, H. (2014). Green machining: Energy and emissions benchmarking in subtractive manufacturing. Journal of Cleaner Production Engineering, 22(5), 401–412.

- Thomas, M. A., & Nayak, K. (2021). Real-time energy audits in multi-stage production cells. Indian Journal of Sustainable Automation, 4(3), 88–97.