

Non-Invasive Cloud-Native Retrofitting of Production Monitoring via Authorized Web APIs: Field Evidence from 50 PLC-Connected Machines

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Abstract

The Brownfield manufacturers may require a dependable production data without altering the current programmable logic controllers (PLCs) or supervisory systems. It is a non-invasive field study on a single site that is conducted using a non-invasive monitoring overlay, which is based on an authorized manufacturing web API to investigate whether counter-derived production indicators can be trusted when there is a communication break. Machine records were acquired by Google Apps Script and state persistence, history and visualization were supported by Google Sheets. The effective telemetry window consisted of 36,600 observations of 50 machines connected to PLC during 732 refresh cycles (12.23 h). The successful cycles all yielded full 50-machine panels, temporal refresh coverage was 99.59, and the average API response time was 1,015.98 ms (95th percentile: 1,528.6 ms). The main result was a data-quality failure, not a timing constraint: there were 5 cycles of fleet-wide communication-loss followed by 245 cycles of restoration transitions that accounted for 99.975% of the unfiltered positive counter-difference total. A communication-sensitive classification was thus used to differentiate between OFFLINE and immediate RECOVERY observations and assessable RUN and STOP comparisons. With 500 offline/recovery observations excluded, 36,100 observations were assessable, and the corrected production-active fraction was 44.55% (machine-cluster bootstrap 95% confidence interval: 35.91%-53.20%). Another 166.58-h execution-log window had 9,943 failed attempts at acquisition, with 9,941 being HTTP 500 responses. These results determine four decision-relevant requirements: rule out recovery artifacts, condition production states based on continuity of communication, differentiate PLC connectivity and production activity, and show collector, source and machine communication health individually. The evidence confirms that minute-scale reporting is feasible in this specific deployment, but not that physical machine states, or that the results can be generalized to other locations, or that there are economic returns.

Keywords: Brownfield manufacturing, Industrial data quality, Authorized web APIs, Communication-aware state classification, Production decision support, Production monitoring, Smart retrofitting, Operational visibility.

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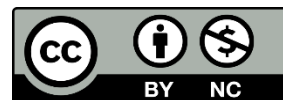
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1. Introduction

The manufacturing manager needs timely and understandable information from the machine to review production, to handle exceptions and to make operational decisions. But legacy equipment, supervisory applications and heterogeneous industrial networks in brownfield factories can make it hard to justify additional monitoring interfaces. Connectivity, cloud analytics, and cyber-physical integration and interoperability (Galloway & Hancke, 2013; Lu, 2017; Yin et al., 2018) are topics of research in the field of Industry 4.0 and Industrial Internet of Things (IIoT). Digitalization can be challenging for small and medium manufacturers, as they may not have the capital, skills, or capacity to implement it (Ghobakhloo et al., 2022; Masood & Sonntag, 2020; Mittal et al., 2018). Smart retrofitting solutions are typically based on the installation of sensors, protocol gateways or edge middleware (Jaspert et al., 2021; Qiu et al., 2020; Hawkrigde et al., 2021). These are applicable where raw signals or protocol translation and/or deterministic processing is needed, and may require plant-side engineering. If data from the machine is already published via an authorized manufacturing application, then it is possible to work with a separate cloud reporting layer instead of the application boundary (Liu et al., 2022; Sauter & Lobashov, 2011). The business question is not just about whether the data can be collected, but whether the indicators that are collected are reliable enough to be interpreted by management. This research evaluates the viability of an existing authorized manufacturing Web API for use as a cloud monitoring overlay acquisition boundary. Google Apps Script makes requests and processes machine records; Google Sheets keeps recent state, historical observations, archival records and displays for management. The collector did not add any PLC programming, field wiring, or industrial database queries or SCADA configuration changes. The deployment also showed one important interpretation problem: The machine counters were temporarily set to lower values when the PLC communication was lost and the initial values were very high, leading to higher positive differences. The unfiltered positive difference sum of the 245 immediate restoration transitions observed fleet-wide was 99.975% from the five immediate restoration transitions observed fleet-wide. If they were considered real output then the production signal would be grossly distorted. Thus, the analysis identifies two different types of continuity: source-data continuity and arithmetic counter change, and compares the successful telemetry window with a window of unsuccessful API calls (execution log).

The main contribution is an empirical demonstration of the mathematical consistency and operational misleadingness of counter-based production indicators when communication continuity is not taken into account. The paper is structured around four findings: the quantified recovery artifact, the corrective OFFLINE/RECOVERY state interpretation, the difference between PLC communication and production activity and a three-layer health distinction between collector execution, upstream API availability and machine/PLC communication. API-reuse architecture is nothing new, it is merely the enabling field instrument. The study raises the question of how these findings might be used for trustworthy non-critical production reporting, but points out that there are no labels for the physical state that can be used independently. These considerations translate into four research questions that guide the observational field study. RQ1: Can existing authorized industrial web-API data be reused to construct a practical near-real-time cloud monitoring layer without modifying the operational control infrastructure? RQ2: What timing performance, refresh stability and record completeness are achieved by the one-minute cloud acquisition process in the observed field deployment? RQ3: How do communication-loss and recovery artifacts affect counter-derived production indicators, and how can a communication-aware state interpretation reduce their distortion? RQ4: How should collector execution, upstream API/source availability, and PLC communication be distinguished when reporting monitoring-system health? There were five interruptions of fleet-wide communication, which resulted in 245 immediate recovery transitions that explained 99.975% of the naive sum of positive counter-data distortions, showing the practical scale of counter-data distortion. An analytical OFFLINE/RECOVERY filter omitted cross-communication comparisons prior to classifying assessable counter movement as RUN or STOP; it is a reusable decision rule whose unobservable edge cases must be validated in the future. Out of 36,350 observations of

communication-online, 20,021 did not increase the counter, which confirms that the PLC label of Running in the API should not be offered as physically produced. The 9,943 failed recorded API calls explain why collector execution, source/API availability and individual PLC communication need to be differentiated, and data freshness is apparent to report consumers. These findings are given the field setting of the 50-machine API-reuse deployment, 732 successful refresh cycles and independent failure-log window. The managerial implication is a reporting-governance principle: machine activity and production summaries must not be considered decision-ready until the source freshness, counter continuity and metric meaning have been verified.

2. Related Work and Research Gap

2.1 Smart manufacturing, IoT and cloud integration

Industry 4.0 goes beyond traditional automation and introduces new concepts of connected production systems in which physical equipment, industrial networks, information systems, and services in the cloud or in the edge share operational information (Galloway & Hancke, 2013; Hästbacka et al., 2022; Liu et al., 2022; Lu, 2017; Mantravadi et al., 2022; O'Donovan et al., 2015; Qiu et al., 2020; Terrazas et al., 2019; Yin et al., 2018). The development of production systems has been growing towards the importance of data availability and flexible coordination (Yin et al., 2018) and the studies on the IIoT and edge-computing have created architectures for low latency data collection, distributed processing and integration with the cloud (Hästbacka et al., 2022; Qiu et al., 2020). When dealing with large scale contexts, industrial big-data pipelines offer structured methods for gaining and holding machine-produced data, and for processing and analysing it (O'Donovan et al., 2015). Cloud-based shop-floor architectures serve as proof of the benefits of elasticity and analytical access on the shop-floor in a centralized manner. Service-oriented IIoT gateways also connect resources on the field level to cloud-manufacturing environments (Liu et al., 2022). Hästbacka et al. (2022) demonstrate how to dynamically compose industrial data and analytical services across edge and cloud resources, whereas Mantravadi et al. (2022) focus on interoperability and information-architecture decisions for the IIoT connected MES/MOM environment. The following approaches are examples of the importance of separating out the acquisition, transport, storage, and application services.

2.2 SME constraints and low-cost monitoring

SME-oriented Industry 4.0 research consistently cautions that technology adoption is constrained by capital, awareness, skills and organizational readiness (Ghobakhloo et al., 2022; Masood & Sonntag, 2020; Mittal et al., 2018). Mittal et al. (2018) argue that SME digitalization cannot simply adopt maturity models designed around large-enterprise resources. Masood and Sonntag (2020) empirically identify financial, awareness and knowledge constraints among UK SMEs, while Ghobakhloo et al. (2022) synthesize drivers and barriers into a transformation roadmap for manufacturing SMEs. Low-cost digital-manufacturing research responds to this gap by matching the sophistication of monitoring technology to the actual operational problem. Hawkrigge et al. (2021) present a “monitoring on a shoestring” approach built around low-cost technologies and modular functions for data collection, computation, communication, analysis, storage and visualization. The implication for the present study is important: if data collection has already been solved by the existing plant application, an incremental monitoring system may only need to add transformation, state processing, storage and visualization. For operational decision-makers, an application-layer overlay is a candidate only when the existing API is authorized, relevant, sufficiently fresh and supported by clear failure-escalation ownership. This study does not measure cost savings or comparative return on investment.

2.3 Smart retrofitting and non-invasive integration

Smart retrofitting aims at enhancing the value of existing assets through the addition of information access and analytic capabilities (Jaspert et al., 2021; Sanchez-Londono et al., 2023). Other work demonstrates various integration boundary aspects, including vision-based extraction of older PLC interfaces (Ling et al., 2026), low-code retrofit workflows (do Nascimento et al., 2026), edge connectivity (Nakakaze et al., 2024), and industrial gateway-based or cloud

manufacturing interoperability (Ji & Xu, 2025; Liu et al., 2022). These methods serve various signal, timing and integration requirements and cannot be directly compared on cost or risk on the basis of the evidence found in this study. This approach is done by attaching above the authorized boundary of the application data and by not introducing any new PLC protocol interface. Its real value is the field analysis of the meaning of counter differences when they are interrupted, rather than the fact that it has a cloud API. While the focus on industrial data quality is largely on the data being acquired ‘on the go’ (Hramov & Pisarchik, 2025; Peixoto et al., 2025), the other four dimensions of data quality are important, too: accuracy, completeness, timeliness and meaningful interpretation. Studies on semantic-interoperability also reveal the significance of maintaining meaning in industrial systems (Abril-Jimenez et al., 2025). The deployment options are also emphasized by scalable cloud/edge manufacturing, and by decision support for SMEs (Briatore & Braggio, 2025; Tanane et al., 2025). However, no direct proof exists in those sources that a false production increment may be added during the period of replacement of a live counter with a communication-loss value and reinsertion of the live counter. When utilizing an authorized web interface (Arroyabe et al., 2024; Sverko et al., 2022), security and ownership of the industrial devices are still relevant. The current research tackles the practical problem of the reporting of observed field data, the explicit interpretation rule without claiming to have been tested and proved to improve the performance of the existing industrial gateway and cloud or cybersecurity solutions.

2.4 Research gap

There is a vast amount of literature on industrial connectivity, edge/cloud architectures and non-invasive retrofitting. The specific problem discussed here is more specific: field evidence of the extent to which the interruption and recovery of communication corrupt cumulative-counter indicators that managers may use in production reports. First, there is relatively little of the cited work that considers the reuse of an already authorized application-level machine-data interface as an instrumentation boundary for non-critical reporting, not as a new industrial control interface. Second, a consistent data panel does not necessarily mean that the successive values of the counter are semantically comparable over an interruption. If there is no explicit continuity rule, recovery can be confused with production. Third, operational dashboards should separate collection execution from source-system availability, PLC communication and counter-derived activity; if these layers are collapsed, they can lead to stale data or to false escalation. This single-site analysis fills these smaller gaps by quantifying the recovery artifacts observed and providing a clear communication-aware interpretation rule. It does not assume that these problems do not exist in previous studies or that the rule proposed is physically verified in plants.

Table 1: Positioning of the present study relative to common brownfield monitoring approaches.

Approach	New plant-side hardware	PLC / protocol engineering	Direct modification risk	OT	Primary value proposition
Direct PLC integration	No/optional	High	Medium-high		Direct, high-fidelity field access
IIoT / edge gateway	Usually	Medium-high	Medium		Protocol translation and edge processing
External sensors retrofit	Yes	Low-medium	Low		Independent sensing without PLC changes
Vision-based extraction	Yes (camera)	Low	Very low		Non-contact extraction from legacy interfaces
Authorized web-API reuse (this study)	No	Low at cloud layer	Very low		Reuse an already established application data path

The qualitative classifications in Table 1 are indicative architectural judgments, not measured comparative cost, cybersecurity or operational-risk estimates. Their suitability depends on local access permissions, data fidelity, system ownership and decision-criticality.

2.5 Field-informed research propositions

Prior smart retrofitting research has focused on making legacy data accessible through gateways, edge middleware, sensors or vision-based extraction (Jaspert et al., 2021; Sanchez-Londono et al., 2023; Ling et al., 2026; do Nascimento et al., 2026; Nakakaze et al., 2024), while IIoT architectures show that application-level access can be separated from the control path (Sauter & Lobashov, 2011; Liu et al., 2022; Hästbacka et al., 2022). Low-cost and SME studies stress matching monitoring to the operational problem under capital and skills constraints (HawkrIDGE et al., 2021; Ghobakhloo et al., 2022; Masood & Sonntag, 2020; Mittal et al., 2018), though security and ownership concerns remain (Arroyabe et al., 2024; Sverko et al., 2022). This literature has not demonstrated authorized API reuse in the field. Therefore, the following proposition has been developed.

P1: *An authorized read-only manufacturing web API can be reused as a monitoring overlay to deliver non-critical production visibility at minute-scale cadence without modifying the PLC, SCADA or field-wiring control path.*

Data-quality research shows that quality is multi-dimensional and that meaning must be preserved across system boundaries (Hramov & Pisarchik, 2025; Peixoto et al., 2025; Abril-Jimenez et al., 2025), and pipeline studies show that acquisition, transport and processing must be explicitly managed (Hästbacka et al., 2022; O'Donovan et al., 2015; Qiu et al., 2020). Yet no study examines whether counter differences remain comparable across communication loss and restoration. Therefore, the following proposition has been developed.

P2: *Counter-derived production-activity indicators are distorted by communication-loss and recovery artifacts, and a communication-aware OFFLINE/RECOVERY exclusion is necessary before counter movement can be interpreted as production activity.*

Industry 4.0 and IIoT work separates acquisition, transport, storage and application services (Lu, 2017; Yin et al., 2018; Liu et al., 2022; Mantravadi et al., 2022; Terrazas et al., 2019; HawkrIDGE et al., 2021), but typically treats communication-online status as evidence of operational presence. Therefore, the following proposition has been developed.

P3: *PLC communication-online status and counter-derived production activity are distinct constructs, and connectivity should not be reported as evidence of physical production.*

Layered architectures and data-quality studies warn that collapsing health dimensions obscures which layer has failed (Hästbacka et al., 2022; Liu et al., 2022; Mantravadi et al., 2022; Terrazas et al., 2019; Briatore & Braggio, 2025; Tanane et al., 2025; Hramov & Pisarchik, 2025; Peixoto et al., 2025). Therefore, the following proposition has been developed.

P4: *Collector execution, upstream API/source availability and machine-level PLC communication constitute distinct monitoring-health layers, and they should be reported separately together with the age of the last valid sample.*

These propositions are interpretive rather than experimentally tested, and the field study examines each against the observed telemetry and execution-log records. These propositions contextualize the data credibility and management reporting as the primary interpretation problems. The experiment documents feasibility of deployment and field artifacts observed, but does not experiment with economic results or accuracy of inferred physical machine states.

3. System Architecture and Implementation

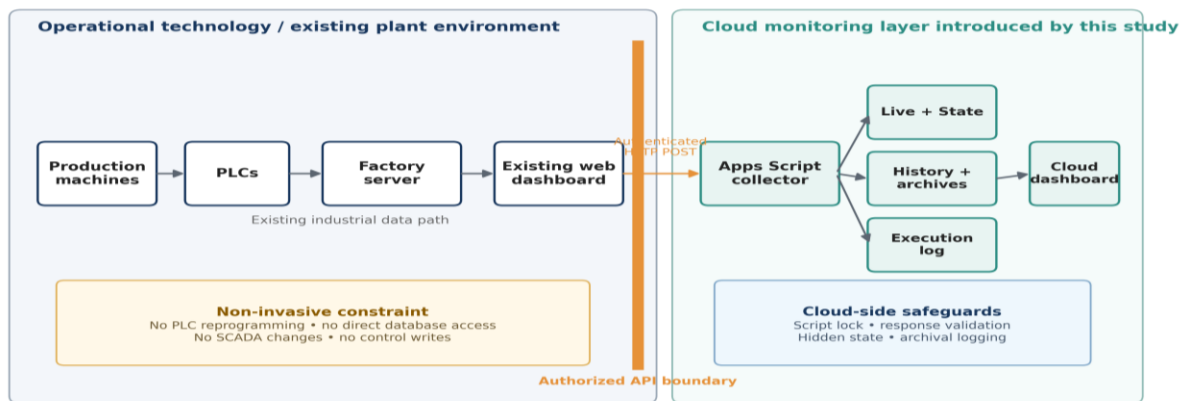


Figure 1: Authorized application-layer monitoring overlay used as the field instrument.

Note: The existing machine/PLC/control path is unchanged; communication-aware interpretation and management-facing data-quality checks are detailed in Section 4.

3.1 Architectural principle

The system isolates the already in place operational technology (OT) path and an additional reporting path. The authorized application-layer monitoring overlay used as the field instrument is illustrated (see Figure 1). PLCs and production machines provide operational information to a set factory server and approved web application. The cloud collector reads records chosen by that application boundary, generates machine level history and computes status indicators, but does not write to PLCs, modify PLC programs, add field wiring, directly query the industrial database or modify SCADA configuration. The methodology thus minimizes intervention in the layer of control in this deployment, yet read-only architecture does not remove the threat of cybersecurity or reliance on the source API. The reporting layer must be seen as a support to non-critical management inspection, rather than a replacement to industrial control, confirmed machine-state sensors or safety interlocks. The functional layers of the deployment and the change introduced at each layer are summarized (see Table 2).

Table 2: Functional layers and their roles.

Layer	Function	Change introduced
Production machine	Physical manufacturing process	None
PLC	Maintains machine variables and cumulative production counters	None
Industrial network	Carries plant-side data	None
Factory server	Receives / stores existing PLC information	None
Existing web application / API	Approved read-only access to existing manufacturing data	Read-only reuse
Google Apps Script collector	Request, validation, parsing, transformation and orchestration	Added
State store	Stores previous valid count, PLC communication label and timestamp	Added
History / archive	Stores timestamped observations	Added
Execution log	Records success/failure and response timing	Added
Cloud dashboard	Displays production movement separately from data freshness and source health (recommended)	Added

3.2 Data acquisition and orchestration

The Google Apps Script collector will make an authenticated HTTP POST request to the current manufacturing API with an application session saved in Script Properties. The implemented workflow checks the response and non-empty body, parses JSON, requires the expected machine array and uses a script lock to avoid overlapping state updates. On a failed acquisition, it records execution status instead of considering the past snapshot as newly seen production. Other security features, like authenticated TLS transport, limited credential lifetimes and automatic freshness alarms, are not features that are proven in the field data, but production-deployment suggestions. The implemented acquisition and validation workflow is shown (see Figure 2).

Acquisition, validation and state-update workflow

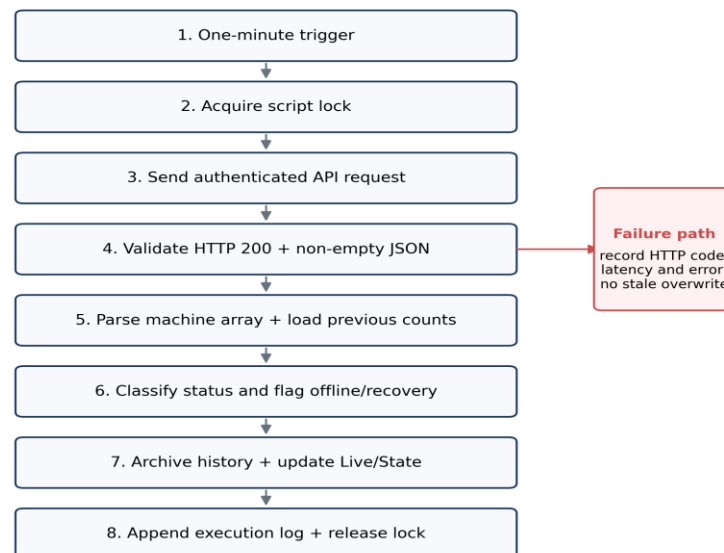


Figure 2: Collector acquisition and validation workflow as implemented.

Note: A failed request is recorded in the execution log; the analytical exclusion of OFFLINE and immediate RECOVERY states is described separately in Section 4.2.

3.3 Data model and archival behavior

The implementation maintains four principal logical datasets: Live, History, State and ExecutionLog. Live is replaced each successful cycle with the newest machine snapshot. History appends timestamped machine observations. State stores the prior count and timestamp required to compare consecutive observations. ExecutionLog records collection start, response receipt, completion time, response code, machine count, API response time, sheet-update time, result and error text. A date-based archival process copies permanent history and log rows to separate archive workbooks while bounding the active workbook size. The machine-observation variables used in the analysis are listed (see Table 3).

Table 3: Machine-observation variables used in the analysis.

Field	Interpretation
Timestamp	Cloud collection time associated with the machine snapshot
Machine Key	Persistent machine identifier
Machine Name	Human-readable machine label (excluded from publication-level analysis)
PLC IP	Plant network identifier (redacted from manuscript outputs)
Machine Type	Operational category: Cutting, Printing or Fabric
Item Name	Current item / product descriptor where available
SCT	Source-system cycle-related field

Field	Interpretation
Current Count	Cumulative machine counter at time t
Previous Count	Persisted cumulative counter from the preceding observation
Count Difference	Current Count – Previous Count
Calculated Status	RUN, STOP or COUNTER RESET under the implemented rule
Total Production Count	Source-system total field
API PLC Status	Communication-oriented status exposed by the API
API Response Time (ms)	Request-to-response latency for the complete refresh cycle

3.4 Security boundary

The prototype was an application session authenticated on plaintext HTTP endpoint. It is a material restriction: non-encrypted transport authentication fails to give an acceptable production security boundary. The deployment in any organization must mandate the use of HTTPS/TLS, accepted read-only credentials, proper service-account policies and management, rotation or revocation of credentials, audit logs and control of archived data and formal OT/IT authorization. Publication outputs do not contain endpoint details, internal addresses, network identifiers and session information.

4. Machine-State Model and Analytical Method

4.1 Original counter-difference rule

Let $C_{i,t}$ denote the cumulative counter of machine i at refresh t , and $C_{i,t-1}$ denote the previous stored count. The observed count difference is:

$$\Delta C_{i,t} = C_{i,t} - C_{i,t-1} \quad (1)$$

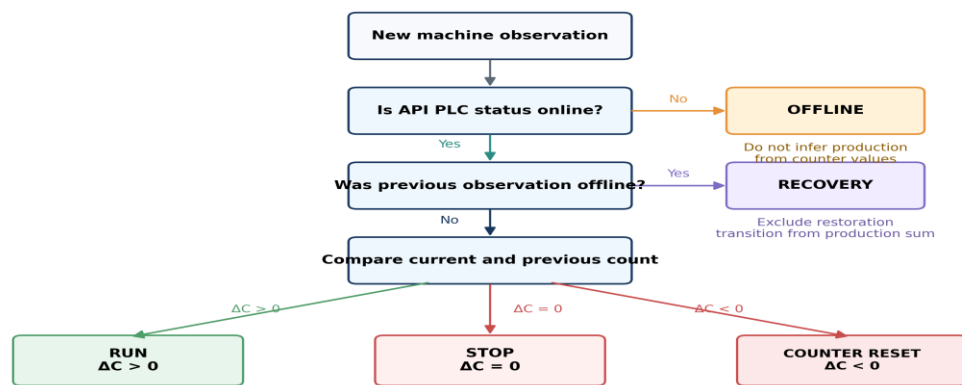
When using numeric observations whose previous stored value exists, the original software identifies a positive change with RUN, an unchanged value with a STOP and a negative change with a COUNTER RESET. INITIAL is a machine with no preceding value and INVALID COUNT is a nonnumeric count. These are not observed physical physical states, but are the labels of arithmetic software. Specifically, the rule fails to separate a bona fide manual reset or rollover and a communication artifact unless other circumstances are provided.

$$S_{i,t} = \text{RUN if } \Delta C_{i,t} > 0; \text{ STOP if } \Delta C_{i,t} = 0; \text{ COUNTER RESET if } \Delta C_{i,t} < 0 \quad (2)$$

4.2 Communication-aware refinement

In five witnessed fleet-wide PLC communication breaks, 49 machine counters in each cycle of affected state future decreased compared to their previous values; the following online reading reinstated the previous cumulative values. A positive difference at restoration can be proved mathematically correct against the temporary offline count but it cannot be evidence of new production. An analysis, which is communication conscious, should thus consider the current and the previous communication labels and then interpret a difference in counts. The analytical communication-aware classification applied to the field records is illustrated (see Figure 3).

Communication-aware machine-state classification logic



Only online-to-online RUN/STOP observations are included in the corrected production-active fraction.

Figure 3: Analytical communication-aware classification applied to the field records.

Note: OFFLINE and first-online RECOVERY observations do not enter the reported RUN/STOP denominator. Rollover, manual reset, and source restart require additional evidence and are treated as proposed safeguards in Table 4.

The retrospective field analysis applied the following order rule: a current PLC-offline record is defined as OFFLINE; the first successive online record is defined as RECOVERY; and the current and previous counts are defined as RUN/STOP, only when the consecutive observed PLC communication statuses are online, and the counter values are readable. The unrecorded OFFLINE/RECOVERY records were not included as zero production. Table 4 formalizes the rule observed and isolates it as not the rest of the edge-case treatment that should be considered in future implementations (see Table 4). The COUNTER RESET label on the original software is held as a negative difference but is not to be considered a confirmed root cause.

Table 4: Ordered communication-aware state decision table and recommended exception handling.

Priority / condition	State or flag	Treatment of counter and reporting	Status in this study
1. API request fails / no fresh machine array	SOURCE UNAVAILABLE	No new machine record; mark the last valid sample stale and report API health separately.	Recommended reporting safeguard; failure-log evidence observed
2. Current PLC communication indicates offline	OFFLINE	Exclude current observation from production-activity denominator and increment sum.	Applied retrospectively; 250 records
3. Current online; immediately prior PLC observation offline	RECOVERY	Exclude the first restored comparison and reset the valid comparison baseline.	Applied retrospectively; 250 records
4. No preceding usable numeric count	INITIAL	Establish a baseline; do not infer RUN or STOP from the first valid count.	Original software label; not independently validated
5. Current or prior count missing / nonnumeric	INVALID COUNT	Do not interpret count movement; retain an error flag pending a valid baseline.	Original software label / proposed caution
6. Consecutive online comparable counts; current > prior	RUN	Count an assessable positive increment; activity only, not verified machine running.	Applied retrospectively
7. Consecutive online comparable counts; current = prior	STOP	Count an assessable unchanged counter; not a verified fault or downtime event.	Applied retrospectively
8. Consecutive online counts; current < prior	COUNTER RESET / UNRESOLVED	Flag a negative difference; do not count it as positive output without determining cause.	Arithmetic label observed; physical cause not validated

Priority / condition	State or flag	Treatment of counter and reporting	Status in this study
9. Suspected rollover; known counter range and wrap evidence	ROLLOVER SUSPECTED	Hold increment for review; only apply modular correction if counter maximum and reset policy are documented.	Proposed safeguard; no independent rollover labels
10. Verified manual reset or source-system restart	REBASELINE	Use maintenance or restart evidence to start a new baseline; do not bridge old and new counters.	Proposed safeguard; no verified event labels

4.3 Performance metrics

Several metrics were defined to avoid conflating distinct failure mechanisms.

Refresh coverage = $N_{\text{observed refresh cycles}} / N_{\text{nominal refresh cycles}} \times 100\%$ (3)

Machine-record completeness = $N_{\text{machine records}} / (N_{\text{observed cycles}} \times M) \times 100\%$ (4)

Communication availability = $N_{\text{online observations}} / N_{\text{total observations}} \times 100\%$ (5)

PAF = $N_{\text{RUN}} / (N_{\text{RUN}} + N_{\text{STOP}}) \times 100\%$ (6)

PAF refers to production-active fraction: the portion of assessable online-to-online machine observations where there is a positive counter difference. It is neither equipment availability, downtime, utilization, fault rate or total equipment effectiveness (OEE). Unscheduled time, setup, changeover, starvation, maintenance and a lengthy production cycle or an existing fault can be reflected by a non-increasing counter. Those reasons cannot be disentangled without production schedules, operator or SCADA ground truth, and agreed counter definitions.

4.4 Statistical analysis

The analysis was conducted directly from the row-level History and ExecutionLog records. The three analytical datasets and their observation windows are summarized (see Table 5). Descriptive statistics were calculated at the refresh-cycle level for API latency and scheduler timing because the same API response time is repeated across all machine rows in a cycle. Machine-level PAF was calculated after communication-aware filtering. A 95% confidence interval for the fleet mean PAF was estimated by nonparametric bootstrap resampling of the 50 machine-level PAF values (10,000 resamples), thereby avoiding the unrealistic assumption that tens of thousands of repeated minute-level observations are independent. Cutting and Printing machine-level PAF distributions were compared exploratorily with a two-sided Mann–Whitney U test; the single Fabric machine was excluded from that inferential comparison. Cliff's delta was reported as a distribution-free effect-size measure. Spearman's rank correlation evaluated whether the number of RUN machines in a cycle was associated with API response time. All inferential analyses are exploratory because production loading was observational rather than experimentally assigned.

5. Experimental Dataset and Field Setup

5.1 Industrial deployment

The field collector asked an authorized existing industrial production-monitoring environment to return the list of 50 machines connected to the PLC, of which 40 are Cutting, nine are Printing and one is Fabric. One complete machine panel was returned in each successful API response and one common value for the response time was stored for the cycle. For this analysis, no extra plant-side sensors or control equipment was added. The site and source-system configuration has not been compared and contrasted with other facilities in an independent way, and the evaluation is therefore a bounded deployment case and not a multi-site validation.

5.2 Separation of non-overlapping observation windows

Two separate time periods from the field workbook were analyzed as two independent samples. The History sheet shows successful telemetry on 31 July 2026 but unsuccessful attempts to collect the data between 6 and 13 August 2026 are recorded in the later active ExecutionLog. The 'completeness' of 7.32% was a miscalculation of the pre-existing Performance summary as it had been combined with the later failure-log window of 166.58-h, which is not a valid quality

indicator for either of the periods. All values reported here were therefore reconstructed for their appropriate observation windows from the corresponding raw History and ExecutionLog records. The second period is a record of failed attempts, and does not reflect independently confirmed continuous failure of the source service.

Table 5: Analytical datasets.

Dataset	Period	Rows / cycles	Primary use
Successful telemetry history	31 Jul 2026, 00:00:18–12:14:17	36,600 machine rows / 732 cycles	Completeness, timing, latency, communication and activity
Live snapshot	31 Jul 2026, 12:14:17	50 machine rows	End-of-window current state
Failure execution log	6 Aug 2026, 21:02:13 – 13 Aug 2026, 19:37:13	9,943 execution attempts	Upstream API failure and scheduler persistence

5.3 Data integrity and validation boundary

The successful telemetry dataset was checked for duplicate timestamp–machine pairs, missing analytical fields, count-difference arithmetic and consistency between stored status and the implemented classification rule. All 36,600 stored Count Difference values exactly matched Current Count – Previous Count, and all 36,600 stored RUN/STOP/COUNTER RESET labels matched the code rule. This verifies software implementation consistency; it does not constitute physical-state classification accuracy because an independent operator or SCADA ground-truth label was not available.

6. Results

6.1 Dataset integrity and refresh coverage

The successful telemetry logs consisted of 732 distinct refresh timestamps and 50 distinct machine identifiers, resulting in 36,600 observations where there were no identical timestamp–machine pairs. The span of 44,038.736-s (12.233-h) of monitoring indicates about 735 nominal refresh opportunities in 60-s interval; 732 successful refresh opportunities thus indicates about 99.59% temporal coverage. All successful cycles were found to have all 50 records on the machine (100% record completeness conditional on successful collection). These coverage measures portray the observed period and cannot be extrapolated to the individual failure-log window. The primary telemetry quality indicators are summarized (see Table 6).

Table 6: Primary telemetry quality indicators.

Metric	Result
Monitored machines	50
Machine types	40 Cutting; 9 Printing; 1 Fabric
Monitoring duration	12.233 h
Nominal refresh interval	60 s
Observed refresh cycles	732
Nominal expected cycles	735
Temporal refresh coverage	99.59%
Machine observations	36,600
Machine-record completeness in observed cycles	100%

Metric	Result
Duplicate timestamp-machine rows	0
Missing Item Name	1,464 rows (4.0%)
Count-difference arithmetic mismatches	0
Stored-status rule mismatches	0

6.2 Scheduler timing stability

Across 731 measured inter-refresh intervals, the mean interval was 60.245 s, the median was 60.050 s and the standard deviation was 6.221 s. The 95th and 99th percentiles were 66.507 s and 76.427 s, respectively. A total of 703 intervals (96.17%) occurred within ± 10 s of the nominal one-minute schedule and 715 (97.81%) occurred within ± 15 s. Four intervals exceeded 90 s; the maximum observed interval was 144.619 s. These results support minute-scale management monitoring but confirm that the platform should not be treated as a deterministic industrial scheduler.

6.3 API response-time performance

Successful API response-time statistics are reported (see Table 7). The distribution of successful API response times across 732 refresh cycles is shown (see Figure 4).

Table 7: Successful API response-time statistics.

Statistic	Response time
Mean	1,015.98 ms
Standard deviation	474.97 ms
Median	916.50 ms
90th percentile	1,393.90 ms
95th percentile	1,528.60 ms
99th percentile	2,232.04 ms
Minimum	492 ms
Maximum	7,057 ms

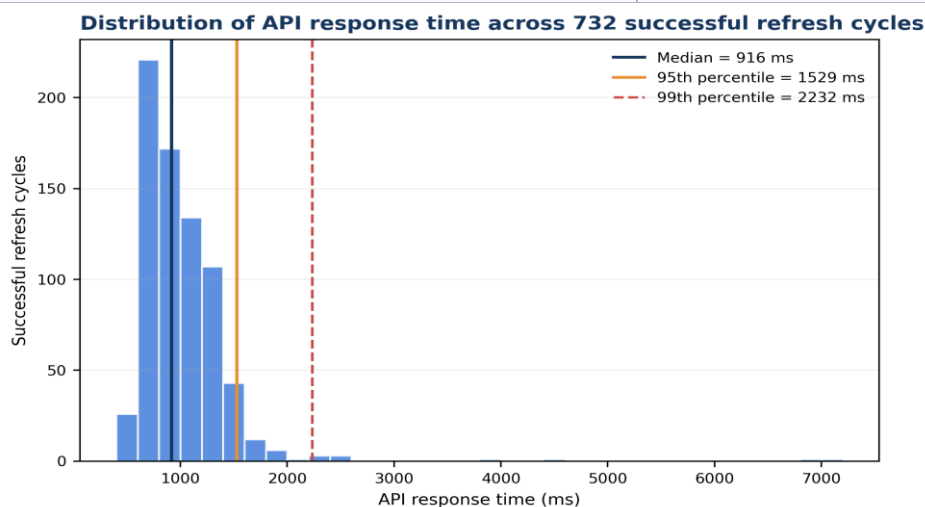


Figure 4: Distribution of successful API response times across 732 refresh cycles.

Note: Latency is analyzed once per cycle rather than repeated across the 50 machine rows.

API response time showed no meaningful association with the number of machines classified as RUN during a successful cycle (Spearman $\rho = 0.030$, $p = 0.421$). Because the request returned the same 50-machine panel irrespective of how many machines were producing, this weak relationship is plausible. The successful end-to-end spreadsheet update delay could not be reconstructed because the later active execution log did not retain the corresponding July success records.

6.4 PLC communication status versus production activity

The API reported 36,350 observations of communication Running and 250 of Offline, indicating machine-observation communication availability 99.317%. The 250 offline observations were all in five synchronized fleet-wide cycles, with each cycle impacting all 50 machines. The successful telemetry window cycles started at about 00:03, 05:34, 06:17, 06:24 and 08:35. Status communication-online and production counter movement are separate observations. Despite the API labeling 36,350 records communication Running, 20,021 of the online records (55.08%) that were labeled communication did not increase their counter. Therefore an online PLC cannot be presented automatically to the managers as a machine that produces. The data do not determine the reason behind each unchanged counter; schedule and operator data would be required to differentiate between planned inactivity and a problem.

6.5 Counter-reset and recovery artifact

In the five cycles of communication-loss throughout the fleet, 49 counters had fallen below their values immediately before, and were marked by the arithmetic rule as COUNTER RESET; one had no further decrease in its count, and was marked with the label STOP. The 49 restored counts in the first cycle after the online cycle gave 245 very large positive differences which the original arithmetic rule termed RUN. The labels in the software were internally consistent with the arithmetic, but the recovery transitions could not be interpreted as normal one-minute output.

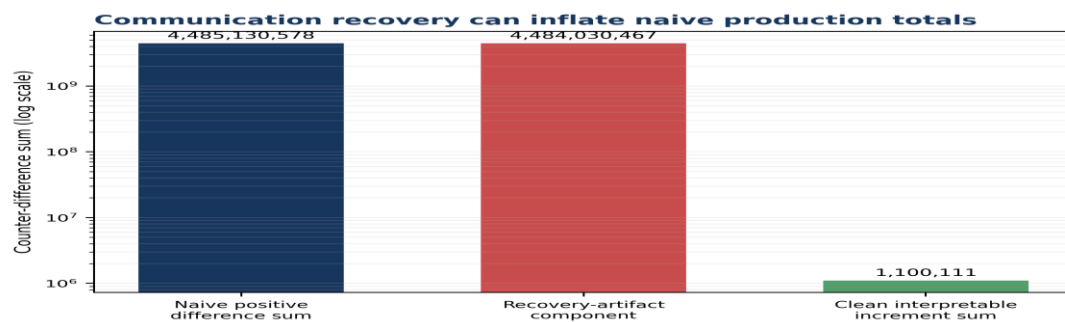


Figure 5: Effect of post-outage restoration on aggregate positive count differences.

Note: The recovery component accounts for 99.975% of the naïve positive-difference total.

The effect of post-outage restoration on aggregate positive count differences is shown (see Figure 5). There were 4,485,130,578 units of positive counts difference in the naive sum of the differences of positive counts across the 36,600-record History dataset. In 245 observations 4,484,030,467 of those units (99.975%) were due to immediate post-offline restoration. Eliminating the five offline cycles and their five successive cycles immediately after the recovery cycles left a positive-increment sum that is interpretable, 1,100,111. The difference between the cumulative count produced by each machine at the end and the first instance was a cross-check of 1,116,221 (around 1.44% higher than the filtered total), which moved around even when no movement was recorded; the difference failed to provide an independent physical production audit. Since Cutting, Printing and Fabric counters are distinct output units, their amounts are only reported as source-counter movement, and cannot be characterized as homogeneous finished-product amounts. A cumulative counter difference is analytically meaningful only when the

integrity and continuity of both compared observations are known. Communication recovery can create a mathematically valid but operationally false production spike.

6.6 Corrected production-active fraction

Communication-aware filtering removed 250 offline observations and 250 immediate recovery observations. The remaining 36,100 online-to-online observations contained 16,084 RUN and 20,016 STOP states. The corrected production-active fraction was therefore 44.55%. The fleet mean calculated from 50 machine-level PAF values was identical, and the machine-cluster bootstrap 95% confidence interval was 35.91–53.20%.

$$\text{PAF} = 16,084 / (16,084 + 20,016) \times 100\% = 44.55\%$$

(7)

The positive count differences among clean RUN observations had a median of 58, a mean of 68.40, a 95th percentile of 136 and a maximum of 719. These magnitudes are several orders of magnitude smaller than the communication-recovery spikes and therefore provide an additional empirical basis for treating the latter as data artifacts rather than genuine one-minute production.

6.7 Machine-level and machine-type activity

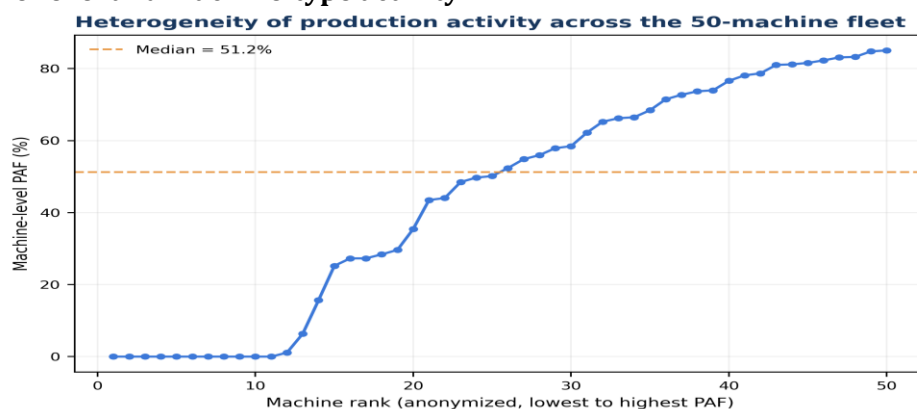


Figure 6: Ranked distribution of machine-level production-active fraction after communication-aware filtering.

Note: Machine identities are anonymized in the publication figure.

The ranked distribution of machine-level production-active fraction after communication-aware filtering is shown (see Figure 6). Machine-level PAF was highly heterogeneous: the median was 51.25%, the first quartile 8.69%, the third quartile 73.44% and the maximum 85.04%. Eleven machines (22% of the monitored fleet) recorded no positive counter movement in any assessable online-to-online interval. These machines cannot be labelled failed from the available data; they may have been unscheduled, awaiting material, in setup, reserved or otherwise intentionally inactive.

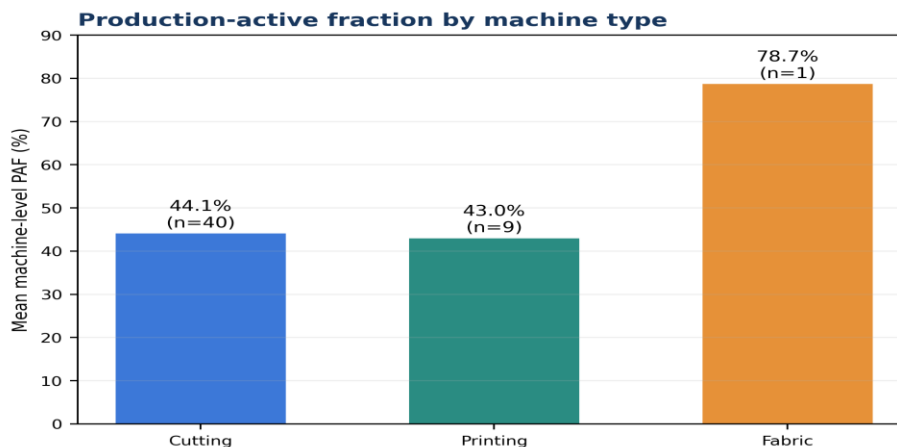


Figure 7: Mean machine-level production-active fraction by machine type.

Note: The Fabric category contains only one machine and is therefore descriptive only.

Table 8: Communication-corrected activity by machine type.

Machine type	Machines	Assessable observations	RUN	STOP	PAF	Positive counter increment sum (source units)
Cutting	40	28,880	12,725	16,155	44.06%	770,385
Printing	9	6,498	2,791	3,707	42.95%	258,687
Fabric	1	722	568	154	78.67%	71,039
Total	50	36,100	16,084	20,016	44.55%	1,100,111

Note: Positive-increment sums are source-counter arithmetic totals; the Cutting, Printing and Fabric groups do not share a verified common unit of finished product.

Communication-corrected activity by machine type is reported (see Table 8). The mean machine-level production-active fraction by machine type is shown (see Figure 7). The exploratory comparison did not detect a difference between machine-level Cutting ($n = 40$) and Printing ($n = 9$) production-active fractions (Mann-Whitney $U = 192.0$, $p = .765$; Cliff's delta = .067). The result does not establish equivalence and is confounded by uncontrolled schedules, loading and product mixes. The single Fabric machine ($n = 1$) is described rather than included in a group-level hypothesis test.

6.8 Temporal activity pattern

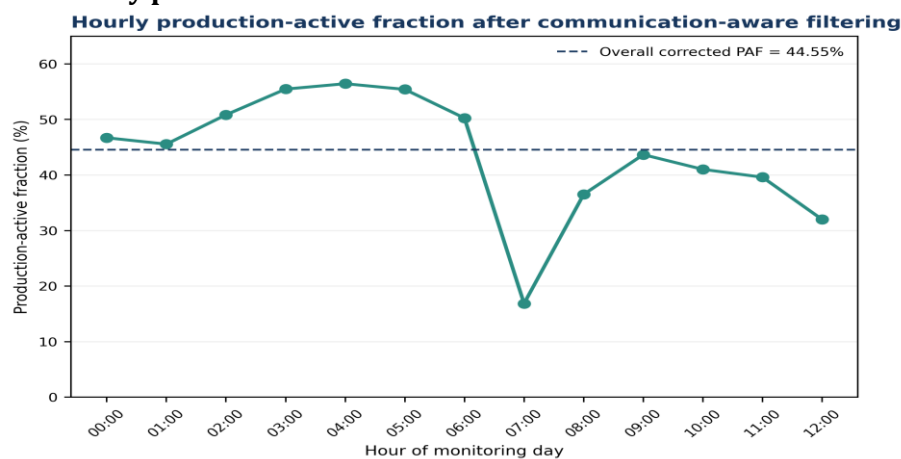


Figure 8: Hourly production-active fraction across the successful telemetry window after excluding offline and recovery observations.

The hourly production-active fraction across the successful telemetry window after excluding offline and recovery observations is shown (see Figure 8). The 12.23-h successful observation period (hourly production-active fraction) was variable. Among complete one-hour bins, the maximum was 56.43% at 04:00-04:59 and the minimum was 16.87% at 07:00-07:59; it rose to 36.52% during 08:00. From 09:00 to 11:59 it ranged approximately 39.6%-43.7%. The 07:00 decrease is something that should be checked against the schedules, changeovers, work orders and material states, but none of the variables related to the context are available here, and one cannot present any causal explanation.

6.9 State persistence

The values of transition were 15,259 RUN-to-RUN, 669 RUN-to-STOP, 681 STOP-to-RUN and 19,191 STOP-to-STOP at contiguous comparisons that were assessable in one minute. Counter-derived state persistence on a one-cycle basis was 95.80% in case of RUN and 96.57% in case of STOP. These are attributes of the observed status labels, rather than measured mechanical reliability or independent evidence of long-term machine operation.

6.10 End-of-window live snapshot

The final live snapshot contained all 50 machines and reported 15 RUN and 35 STOP states, corresponding to an instantaneous production-active fraction of 30%. All 50 machines were communication-online at that snapshot. This further illustrates the distinction between PLC communication health and production movement.

6.11 Upstream API failure window

The later ExecutionLog covers 166.58 h from 6 August to 13 August 2026 and contains 9,943 failed collection attempts. No successful machine arrays were recorded in the available active log during this period. Of these failures, 9,941 (99.98%) were HTTP 500 responses (see figure 9 and table 9); one was an address-unavailable error and one was a timeout. All attempts returned zero machines.

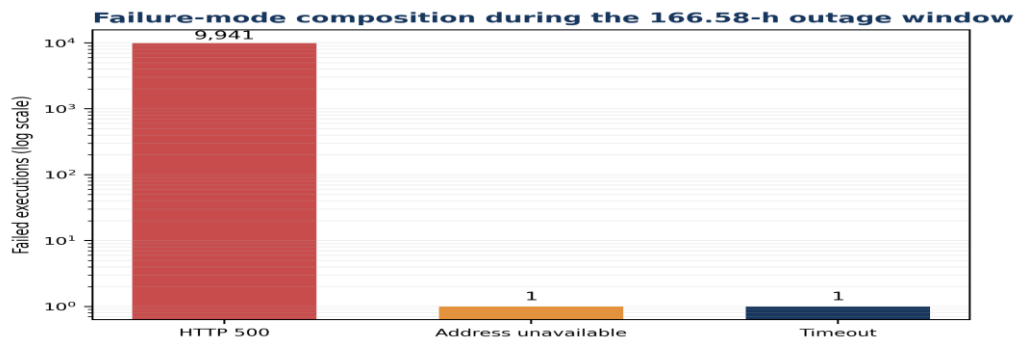


Figure 9: Failure-mode composition in the 166.58-h execution-log window.

Note: The logarithmic scale is used because HTTP 500 failures dominate the distribution.

Table 9: Failure-window performance.

Metric	Result
Logged duration	166.58 h
Failed executions	9,943
HTTP 500 failures	9,941 (99.98%)
Address unavailable	1
Timeout	1
Median failed-request response time	475 ms
Mean failed-request response time	553.54 ms
95th percentile	880 ms
99th percentile	1,552 ms
Maximum	11,832 ms
Median interval between attempts	59.997 s
Maximum interval between attempts	900.185 s
Approx. nominal attempts	9,996
Execution-attempt coverage	99.47%

The two eras disclose various layers of reliability of monitoring. The cloud scheduling and error-logging processes were kept to run with almost a minute cadence in the later period, but no valid machine snapshots were found in the retained execution log. The dashboard facing management should thus differentiate (1) collector heartbeat, (2) last successful API/source response and (3)

PLC communication and last validated machine observation. In this study, such proposed health and freshness indicators were not individually usability-tested.

6.12 Proposition-level synthesis

The evidence supports P1, since 732 successful refresh cycles delivered full 50-machine panels at 99.59% temporal coverage and 100% record completeness with no plant-side hardware or control-path modification. P2 is strongly supported: 245 immediate recovery transitions accounted for 99.975% of the unfiltered positive-difference sum, and excluding OFFLINE and RECOVERY observations reduced the production-active fraction to a corrected 44.55% (bootstrap 95% CI 35.91%–53.20%). P3 is supported, as 20,021 of 36,350 communication-online observations showed no counter increase, confirming that PLC connectivity and production activity are distinct. P4 is supported as a necessity claim: the 166.58-h failure window recorded 9,943 failed attempts while the collector continued executing at near-minute cadence, demonstrating that collector execution, source availability and PLC communication must be reported separately, although the proposed health indicators were not usability-tested.

7. Discussion

7.1 Theoretical implications

The methodological contribution is to demonstrate empirically that consistent arithmetic and successful connectivity do not lead to valid production-state interpretation. Many of the references cited in the retrofit literature are directed at making the data available from the old system accessible. This field case illustrates the need to ensure comparability of successive observations prior to converting them into management indicators. The quantitative restoration artifact presented is a concrete failure mode of the cumulative-counter monitoring, but the study does not assert that it is a completely validated new theory of a state of industrial production.

The OFFLINE and first-online RECOVERY classifications establish a clear distinction between the assessment of communication quality and the inference of production activity. This is consistent with the literature regarding contextual data quality and semantic interoperability (Abril-Jimenez et al., 2025; Hramov & Pisarchik, 2025; Peixoto et al., 2025). The resulting field rule is clear and verifiable, it is not validated as to whether it can detect manual resets, counter roll-over, source restarts or true machine faults.

7.2 Managerial implications

The primary potential value to manufacturing management is to exclude inaccurate production signals from the routine performance review process. When a plant requires minute-scale visibility, but the source is known to be reliable and approved, reusing an authorized API may be appropriate, consistent with low-cost monitoring arguments that match monitoring sophistication to the operational problem (Hawkrigde et al., 2021). The study did not include measures of decision time, installation cost, return on investment or financial losses avoided, however. The following control questions should therefore be explicit on a decision-ready dashboard. First, management should establish whether the machine-data interface is formally authorized for read-only use and who authorizes credentials and data retention, because authorized web interfaces raise security and ownership concerns even when the control path is untouched (Arroyabe et al., 2024; Sverko et al., 2022). Second, the dashboard should report when the collector ran, when the API last returned valid data and who should be alerted for an outage, since the 166.58-h failure window contained 9,943 failed attempts, of which 9,941 were HTTP 500 responses, while the collector continued to execute at a near-minute cadence. Third, it should clarify whether "PLC Running" refers to connectivity or output and confirm that OFFLINE and RECOVERY records are excluded from production reports, because 20,021 of 36,350 communication-online observations showed no counter increase and the 245 recovery transitions accounted for 99.975% of the unfiltered positive-difference sum. Fourth, the locally accepted age for a last valid sample to be considered stale, and the point at which a manager must sign off with plant personnel, should be defined in advance, given that the successful window achieved 99.59% temporal coverage while the later window produced no valid machine arrays

for 166.58 h. Fifth, management should specify which schedules, work orders, operator logs and independent measurements are needed before claiming downtime, utilization or lost production from counter movement, because the corrected production-active fraction of 44.55% (bootstrap 95% CI 35.91%–53.20%) is an activity indicator rather than a validated downtime, utilization or OEE measure, and the 07:00 decline to 16.87% cannot be causally explained without contextual data. Sixth, access controls, archive retention and the reporting platform should be assessed against the anticipated fleet size and approved operational use, since a 50-machine fleet at one-minute cadence would generate approximately 72,000 rows per day and the spreadsheet historian is not proven to scale (Briatore & Braggio, 2025; Tanane et al., 2025). The overlay is not intended to be a substitute for PLC/SCADA control functions, industrial safety mechanisms, nor for operating state measurements that are independently validated.

7.3 Feasibility of the authorized API-reuse boundary

The success of the July telemetry window proves the feasibility of this specific application-boundary integration: the collector received full 50-machine panels at nearly 1-minute cadence and 95% of the API responses were successful, with no new field hardware. Failure of the upstream source to return usable records is shown in the later failure-log window, where a running collector is not enough. The approach is applicable only when data access is authorized, freshness is required and the source is reliable, and when the need for data is not critical for decision making; it was not evaluated in terms of comparative operating cost or comparative risk. This is important because the risk of integration is highly dependent on the location of the retrofit. When raw signals, deterministic control, high-frequency events or protocol translation is needed, direct PLC and gateway solutions are required. However, the capabilities may be greater than the problem requirement for management visibility. When the data needed is provided with less OT interference, an application-layer reuse architecture can be appealing. The study does not claim that web-API reuse is the best solution for industrial gateways as a whole, but rather that it could be the most disruptive-free choice under a certain decision condition.

7.4 The main methodological lesson: continuity of data before arithmetic

The key methodological point is that there has to be continuity before using the counter arithmetic. The negative numbers at communication loss and the large positive numbers at restoration were calculated correctly by the original software, but these were not directly recognizable as production during the transition. Those artifacts were excluded by the retrospective OFFLINE and RECOVERY exclusion, which did not dominate the reported positive-increment sum. The observed rule is made explicit in Table 4 and conservative handling of manual reset, rollover and source restart is suggested. The additional exception types were not separately identified in the study; in an operational deployment, uncertain increments should be considered for review, the last valid time stamp should be retained, and approved counter specifications, restart flags and maintenance records should be used, if available.

7.5 Why it is not machine RUN when it is “PLC Running”

Communication, not proven physical production: 36,350 observations were available on the API but 20,021 of those had no positive counter change. The manager-facing reporting should then differentiate collector execution, upstream API response health and PLC connectivity and derived production activity. A connectivity alert should not be displayed as a machine mechanical failure, and a stale snapshot should not be displayed as a live snapshot without the last valid timestamp.

7.6 Operational interpretation of the 44.55% PAF

The 44.55% PAF is operationalized as: The corrected fleet production-active fraction is a metric that reflects the percentage of observations of online-to-online machines with increasing cumulative counts that are assessable. Not measures utilization, downtime, equipment availability, performance losses or OEE. The variability around 07:00 may lead to checking schedules or production context by a manager, but the data provided cannot determine the cause of the variability. The organization would have to have verified counter definitions, planned

operating time, work orders, reasons for inactivity and independent physical-state validation prior to using the metric in formal operational or financial reporting.

7.7 Failures and graceful degradation

The separate execution-log period reveals that data collection and acquisition of usable machine records are two distinct results. Near minute collector activity resulted in the logging of the 9,943 unsuccessful calls. A production dashboard shouldn't just sit there: suggested protections are to include a collector heartbeat, API-response status, age of last valid data and machine-level communication state. In this field study, the impact of retries and backoffs on unnecessary requests during source failures was not examined, nor was the impact of operator responses.

7.8 Scalability

With 50 machines and 1 successful observation per minute, a 24 hour uninterrupted collection would produce ~72,000 machine rows per day (50 x 60 x 24). The growth of the active sheet during a prototype trial can be reduced by date-based archives, but this is not a proof of long-term scalability of spreadsheets. If the fleet is larger or sampling is more frequent or the retention is longer, then a storage-capacity and governance assessment may be needed, and a database, data warehouse or industrial historian may be required, with spreadsheets being the primary reporting tool.

7.9 Security and governance

Minimizing intervention in the PLC control path does not remove information-security responsibilities. The prototype's plaintext HTTP transport is a significant deployment limitation. An enterprise implementation should require TLS/HTTPS, formally approved least-privilege read-only service authorization, auditable credentials, retention controls, ownership of archives and restricted distribution of plant identifiers. The integration depends on an authorized pre-existing information path and must never bypass plant access-control procedures. These are deployment requirements; the field data do not demonstrate compliance with them. A deployment decision guide summarizing indicative suitability by requirement is provided (see Table 10).

Table 10: Deployment decision guide. Suitability ratings are author judgments rather than measured cost or risk comparisons.

Requirement / condition	Indicative suitability (judgment)	Reason
Minute-scale management visibility	High	Observed timing supports non-critical near-real-time monitoring
No permission to change PLC logic	High	Architecture begins above the control layer
Existing authorized machine-data web service	Essential	Primary data source for the approach
Sub-second deterministic control	Low	Cloud trigger and web API are nondeterministic
Safety-critical interlocks	Not suitable	Monitoring layer must not replace industrial control
High-frequency vibration / waveform analytics	Low	Source API and spreadsheet cadence are insufficient
Large fleet / long-term history	Medium	Collector concept scales, spreadsheet historian does not
Weak or unstable upstream API	Low-medium	Source dependency becomes dominant failure mode

8. Conclusion

This single-site field study tested a non-invasive production-reporting overlay that gathered machine data using a standard web API for manufacturing available to the authorized manufacturer, without altering the PLC/SCADA control path. During the successful telemetry window of 12.23 hours, the collector received 36,600 records from 50 machines in 732 successful refresh cycles, with 99.59% nominal temporal coverage and complete machine panels in observed refresh cycles. The major contribution was the evidence that communication recovery, not real one minute output, was the primary contributor to the positive-difference sum, which was 99.975% of the unfiltered positive-difference sum, and comprised 245 restoration transitions. Removing OFFLINE and immediate RECOVERY observations yielded 36,100 recoverable observations that resulted in a corrected production active fraction of 44.55%. The 166.58-h failure-log window was separated, with 9,943 requests failing, emphasizing the importance of separating collector execution, upstream data availability, and PLC communication. Managers should ensure that they check the freshness, communication continuity and indicator definitions before making use of these records in production reviews. The evidence is restricted to a single industrial application, a single short successful telemetry window and a different unsuccessful-request window. There were no independent physical-state ground truth, multi-site validation, counter rollover/manual-reset labels or measured economic outcome. Consequently, the study supports a bounded interpretation method and a feasible reporting integration for non-critical decisions, not validated machine downtime, OEE, cost savings or general superiority to other architectures. Future testing should consider exception-state logic against operator and SCADA records from different sites and introduce secure transport, approved credentials, stale-data alerts and scalable storage.

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