



Measuring Maintenance Labor Demand from Incomplete Event Logs in Private Manufacturing

Rai Ichlas Rifansyah¹, Muhammad Iqbal Ismail^{1*}

¹Department of Management, Universitas Pamulang, South Tangerang, Indonesia

*Corresponding author e-mail: dosen03423@unpam.ac.id

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ABSTRACT

Maintenance activity records are often used to justify staffing decisions even when they capture only part of the work performed. This article examines the conditions under which such records can support defensible estimates of labor demand. A bounded documentary analysis of a privately supplied manufacturing internship report was combined with a focused narrative synthesis of maintenance management, data quality, workforce planning, and research ethics literature. The analysis distinguished elapsed event time, individual participation time, observed labor demand, and workforce capacity. The report supported a description of recorded maintenance activities but did not establish complete work coverage, individual participation intervals, or a common observation horizon for demand and capacity. These limitations prevent a defensible staffing estimate. A proposed measurement procedure therefore retains unknown durations, records changes in crew participation, reconciles work and capacity over the same horizon, and separates operational calculation from disclosure decisions. A fully synthetic example illustrates how elapsed time multiplied by nominal crew size can overstate labor consumption while incomplete recording can understate total demand. No company identifiers or operational quantities are disclosed. The contribution is a transparent procedure for deciding which workload statements the available evidence permits. Its practical effectiveness remains to be evaluated through prospective observations with documented publication authorization.

Keywords: person time; temporal alignment; data completeness; workforce planning; confidentiality

1. INTRODUCTION

A maintenance record can show that a repair took place without showing how much labor the repair consumed. The distinction matters when managers use those records to allocate technicians, compare preventive and corrective work, or argue for a change in staffing. A job may remain open while a technician waits for a component, assists another job, or takes an authorized break. A second technician may join only for a difficult part of the repair. Treating the interval between opening and closing a record as uninterrupted labor therefore requires evidence that the record itself may not contain. Maintenance management and performance measurement research place information quality within a wider set of operational and organizational requirements (Garg and Deshmukh, 2006; Tsang et al., 1999; Parida et al., 2015).

The growth of predictive maintenance has increased the value placed on operational data. Reviews describe substantial developments in failure diagnosis, remaining useful life prediction, and maintenance optimization (Jardine et al., 2006; Lei et al., 2018; de Jonge and Scarf, 2020). Reviews of machine learning applications likewise organize an extensive body of methods for predicting equipment condition (Carvalho et al., 2019; Zonta et al., 2020). These advances do not remove the need to define the labor quantity being estimated. A record suitable for identifying a failure mode may be unsuitable for measuring a technician's contribution to a job. Prediction of equipment deterioration and estimation of labor demand are related management problems, but their data requirements differ.

This problem is particularly visible when an internship or a short workplace study becomes the basis for an academic article. Activity tables may provide useful operational observations while omitting the sampling frame, interrupted work intervals, or the relationship between

the observation period and a capacity denominator. Such omissions restrict the inference that can be made from the document; they do not establish that the organization has poor maintenance practices. Research on maintenance work orders shows why analytical purpose must guide the assessment and cleaning of records (Hodkiewicz and Ho, 2016; Conte et al., 2021). Local workload studies also demonstrate the use of activity observations in production and maintenance settings, although their assumptions and observation periods must be examined before their staffing conclusions are transferred to another case (Widhiarso et al., 2022; Jumali et al., 2025).

The present article asks three questions. Which labor quantities can be established from the supplied report? Which missing or ambiguous fields prevent a defensible comparison between demand and capacity? How can the resulting methodological lessons be reported without exposing a private organization's operational information? The objective is to develop an explicit sequence of measurement and reporting decisions. It is not to estimate the firm's optimal headcount, evaluate named workers, or claim that a new data collection system has already improved performance.

The contribution is deliberately limited. Data quality, event log imperfections, and maintenance measurement are established topics. This analysis brings them together around a specific decision: whether a set of activity records supports only a description of observed work, an estimate of period demand, or a staffing analysis. It also treats confidentiality as a limit on what can be published, while preserving enough methodological detail to reproduce the calculations. The article combines documentary findings with a proposed procedure and a separate synthetic example. The synthetic values are illustrative inputs rather than substitutes for undisclosed company results.

2. LITERATURE REVIEW

2.1. Maintenance policy and labor demand

Time based, condition based, and corrective maintenance differ in how work is triggered and scheduled (Ahmad and Kamaruddin, 2012; Alaswad and Xiang, 2017). Their labor requirements cannot be inferred solely from the number of work orders in each category. A brief intervention involving several workers can consume more labor than a longer intervention performed by one worker. The timing of demand also matters: planned work can sometimes be shifted, whereas an urgent failure may require a particular skill immediately. Maintenance optimization provides models for evaluating policies under stated assumptions, but a model's decision variables should not be confused with quantities that an incomplete log has actually measured (de Jonge and Scarf, 2020).

The literature on smart maintenance broadens the discussion beyond sensors and algorithms. Work on future maintenance scenarios and empirical conceptualization identifies organizational capabilities, people, and integration as part of the maintenance function (Bokrantz et al., 2017; Bokrantz et al., 2020b). Its research agenda also makes clear that management arrangements require investigation alongside technological developments (Bokrantz et al., 2020a).

For labor measurement, this suggests a practical starting point: establish consistent records and shared definitions before using a more elaborate analytical system. Reviews of machine learning, reasoning approaches, and digital twins provide technological context, but do not validate a headcount estimate derived from unsegmented work intervals (Çinar et al., 2020; Dalzochio et al., 2020; Errandonea et al., 2020).

2.2. Fitness of data for the intended decision

Data quality concerns more than whether a field has been transcribed correctly. A value may be accurate yet incomplete or unsuitable for the intended use. The distinction between intrinsic and contextual quality is central to established data quality research (Wang and Strong, 1996). Assessment methods consequently need to address both the properties of the data and the requirements of the decision (Pipino et al., 2002; Batini et al., 2009). In this article, fitness for use means that the recorded quantity, the population of work, and the time horizon correspond to the workload statement being made.

Maintenance research supplies concrete reasons to apply this principle. Reporting procedures can be assessed as sources of data quality problems, and improvement frameworks connect historical data cleaning with changes in future recording practice (Madhikermi et al., 2016; Lukens et al., 2019). Structured categories are useful, but their apparent precision can conceal a mismatch between the available labels and the work a technician needs to describe (Sexton et al., 2019). Ontology based approaches address the meaning of maintenance activity terms, while recent work connects data quality management to equipment failure risk estimation (Woods et al., 2024; Kang et al., 2024). Semantic consistency can improve interpretation; it cannot recover an unobserved active work interval without further evidence.

2.3. Event time and resource participation

Process mining research offers useful distinctions between events, cases, resources, and the traces that connect them (van der Aalst, 2016). Event log quality problems have been documented as recurring patterns rather than isolated spreadsheet errors (Suriadi et al., 2017). Timestamp imperfections are especially relevant when performance measures depend on duration (Fischer et al., 2020). Preprocessing reviews and studies of practical remedies show that cleaning choices need to match the particular defect being addressed (Marin-Castro and Tello-Leal, 2021; Dakic et al., 2023). Repairing a missing label is different from reconstructing the time for which a worker was actively present.

These findings support a cautious approach to maintenance logs. A start and finish pair can establish an elapsed interval, but labor demand requires resource participation within that interval. Completion timestamps may be administrative entries rather than direct observations of hands-on work. Improvements in analytical software do not resolve this measurement problem automatically, a concern consistent with the emphasis on data quality in process mining research (Bose et al., 2013).

The relevant unit for direct labor is a person minute or person hour, with an explicit rule for interruptions and shared work.

2.4. Capacity and the human dimensions of workload

Performance frameworks connect maintenance indicators with the purposes they are intended to serve (Muchiri et al., 2011; Van Horenbeek and Pintelon, 2014). A labor consumption measure describes an input; it does not, by itself, establish effectiveness, safety, service quality, or an efficient staffing level. Personnel scheduling research considers constraints such as shift coverage and assignment feasibility, while workforce planning research explicitly incorporates skills (Van den Bergh et al., 2013; De Bruecker et al., 2015). Average labor demand therefore supplies only part of the information needed to design a workable maintenance roster.

Queueing theory explains a further limitation. Relationships between arrivals, work in a system, and waiting time require defined processes and assumptions (Little, 1961). Heavy traffic results show why proximity to capacity can affect waiting behavior in relevant queueing models (Kingman, 1961). Neither result is estimated for the present case. They justify treating response requirements and variability as separate questions that remain after a valid labor total has been calculated. Readiness for urgent work should not automatically be interpreted as wasted time.

Time consumption is also narrower than human workload. Research on multiple resources and mental workload addresses demands on attention that are not represented by a task's duration alone (Wickens, 2008; Young et al., 2015). NASA-TLX is an example of a separate workload measurement approach, not a quantity that can be reconstructed from maintenance timestamps (Hart, 2006). Human factors research in Industry 4.0 likewise calls for the joint consideration of people and production systems (Neumann et al., 2021).

The current analysis therefore uses the term labor demand for person time and makes no claim to measure fatigue, cognitive workload, or the health effects of a maintenance assignment.

2.5. Disclosure and methodological transparency

Removing a company's name is insufficient if exact dates, equipment codes, distinctive organizational descriptions, or combinations of operational quantities still identify the site. Research on anonymization and confidentiality illustrates the tradeoff between contextual richness and protection from deductive identification (Saunders et al., 2015; Kaiser, 2009). Those studies concern human participants; their confidentiality reasoning is applied here by analogy to workplace records, without asserting that the contexts are identical. The FAIR principles support well described and reusable research objects, but do not require unrestricted public release of sensitive source material (Wilkinson et al., 2016). A reproducible method can therefore be accompanied by an openly described synthetic example while access to the original document remains restricted.

3. RESEARCH METHODOLOGY

3.1. Design and documentary material

The study is a methodological case analysis using one privately supplied internship report as its documentary case. The report concerned maintenance activities in an Indonesian manufacturing organization. The analysis used the report narrative, embedded activity tables, workload calculations, and descriptions of work scope. The underlying maintenance database, original observation sheets, and staff rosters were not supplied. Documents mentioned in the report were treated as reported context, not as independent sources that had been inspected. Documentary analysis was chosen because the research questions concern the evidential meaning and analytical limits of an existing record (Bowen, 2009).

The report described a broader internship period, but its displayed quantitative activity tables concerned a single observation date. The internship period was not treated as a period of complete quantitative surveillance. The report did not establish a probability sample of jobs, a complete census of technicians, or independent repeated observations across operating conditions.

The analytic unit was the maintenance activity record and its associated measurement assumptions. An activity count is not a count of distinct participants. No additional interviews, experiments, or field observations were conducted for this article.

Case based reasoning can clarify mechanisms and expose assumptions without estimating population parameters (Flyvbjerg, 2006). Here, the purpose is narrower still: to inspect whether the reported fields support particular workload claims. No causal effect, prevalence estimate, or comparative firm performance measure is inferred. Reporting decisions draw on the general transparency principles of observational research, including clear definitions of variables, sources, and missing information (von Elm et al., 2007). This use does not constitute a claim of full STROBE compliance or transform a documentary analysis into a prospective observational study.

3.2. Literature selection and reference verification

The literature component is a focused narrative synthesis. Public scholarly searches and publisher or research institution pages were used to identify work on maintenance labor, work order quality, event log preprocessing, staffing, and confidentiality. Crossref records were used to match titles, authors, publication details, and digital object identifiers. Foundational studies were retained where they define a measurement concept; more recent studies were selected for maintenance information systems and data quality. The final reference set contains 52 sources. Bibliographic verification establishes the identity of a source, not that every source has an equivalent level of evidence.

The selection was purposive rather than an exhaustive database search. No claim is made to have searched the full Scopus or Web of Science collections, applied a preregistered protocol, or completed a systematic review. The distinction between review purposes follows

methodological guidance on literature reviews (Snyder, 2019). Explicit aims, source relevance, and transparent reasoning were emphasized, consistent with the concerns addressed by SANRA (Baethge et al., 2019). SANRA was used as reporting guidance; no formal numerical quality score was assigned. Public abstracts and accessible article content supported the scope of the claims, and no detailed empirical result from an inaccessible full text was reconstructed.

3.3. Extraction and analytical procedure

The document was examined for maintenance category, the meaning of start and finish times, crew information, treatment of interruptions, work scope, and the period attached to capacity.

Repeated presentations of the same table were not treated as additional observations. The analysis first checked the internal arithmetic of the reported activity calculations. It then examined the assumptions needed to interpret those calculations as person time and compared those assumptions with the information actually recorded. Finally, it assessed which conclusions would remain supportable after sensitive details were removed.

Each issue was classified as supported, conditional, or not established. Supported means that the report explicitly documents the feature. Conditional means that a quantity can be calculated only under an additional stated assumption. Not established means that the document lacks the evidence needed for that conclusion. The classification describes evidential status and is not a numerical maturity score. Table 1 presents the resulting audit at a level that does not disclose operational quantities. Internal consistency checking is not independent field validation: no interobserver reliability, member checking, interview triangulation, or instrument validation was performed.

Table 1. Documentary evidence and permitted interpretation

Audit dimension	Evidence in the supplied report	Permitted interpretation
Maintenance categories	Corrective and preventive activities are distinguished.	Supported description of categories recorded in the document.
Crew participation	Crew counts are provided; individual joining and leaving intervals are not.	Person time is conditional on continuous participation.
Interrupted work	A job window is explicitly distinguished from continuous work.	Its active duration remains unknown rather than zero.
Work coverage	The described responsibilities extend beyond the timed activity subset.	Completeness of period labor demand is not established.
Time horizon	Activity observations and schedule capacity use different horizons.	A staffing ratio is not established.
External validation	Underlying logs and independent measurements were not supplied.	Internal consistency can be inspected; field validity cannot be confirmed.

3.4. Definitions and calculation rules

Elapsed event time is the interval between a job's recorded start and finish. Active participation time is the sum of intervals during which an identified worker contributes to the job within the defined scope. An interval spent waiting is not automatically excluded from all labor

measurement: if a technician must remain assigned and unavailable for other work, that interval should be recorded as assigned waiting under an explicit rule. This article distinguishes direct execution from support and assigned waiting so that their treatment can be traced. Table 2 defines the quantities used in the proposed procedure.

Table 2. Quantities and the evidence required to interpret them

Quantity	Unit	Minimum evidence
Elapsed event time	minutes	Recorded event start and finish with known timestamp meaning.
Direct event labor P_i	person-minutes	Active intervals for every participating worker; no duplicate person intervals.
Direct period demand D_i	person-minutes	Eligible event labor clipped to the same declared horizon.
Support and assigned waiting G_i	person-minutes	In-scope time recorded separately and counted once.
Workforce capacity C_i	person-minutes	Roster, breaks, and unavailable time for the same workforce and horizon.
Labor equivalent $N_{e,q,t}$	technician equivalents	Complete in-scope demand and an explicit per-technician capacity.

For activity i , let J_i denote the participating workers and R_{ij} the recorded active intervals of worker j . If interval r begins at s_{ijr} and ends at e_{ijr} , direct labor demand P_i is given by Equation 1. Times must use the same unit, and overlapping intervals for the same worker must be resolved before aggregation.

$$P_i = \sum_{j \in J_i} \sum_{r \in R_{ij}} (e_{ijr} - s_{ijr}) \quad (1)$$

The familiar duration multiplied by crew size calculation is a special case. It is valid only when the stated number of technicians each participates throughout the same uninterrupted interval. A nominal crew count alone does not establish that condition. When an active interval is missing, the record retains an unknown value rather than receiving a zero, an average duration, or the full job window. Any subsequent imputation would require an explicit model and a separate uncertainty assessment; none is applied here.

For a common horizon T , direct demand D_T is the sum of eligible horizon-clipped values $P_{i,T}$. Each $P_{i,T}$ is obtained by applying Equation 1 to the intersections of active intervals with T ; I_T denotes the set of eligible events. Total in-scope labor demand L_T also includes documented support and assigned waiting G_T that have not already been counted. Capacity C_T is computed for the same workforce J_T and horizon from scheduled time $S_{j,T}$, less breaks $B_{j,T}$ and other unavailable time $U_{j,T}$. Equations 2 and 3 express these accounting relationships.

$$D_T = \sum_{i \in I_T} P_{i,T} \quad ; \quad L_T = D_T + G_T \tag{2}$$

$$C_T = \sum_{j \in J_T} (S_{j,T} - B_{j,T} - U_{j,T}) \tag{3}$$

The same activity must not be included both in G_T and in a capacity deduction. Training, for example, can be treated as part of a broad work scope or as unavailable time for a narrower execution scope, provided the choice is explicit and consistent. A nominal schedule after official breaks should not be described as measured productive capacity unless attendance, work scope, and other relevant exclusions have also been reconciled.

A workload to capacity ratio can be calculated using Equation 4 only when L_T represents the intended scope sufficiently completely and C_T is positive and comparable. Dividing L_T by a documented per-technician capacity c_T gives a labor equivalent $N_{eq,T}$. The latter is a workload accounting quantity, not an optimal or automatically feasible headcount.

$$\rho_T = \frac{L_T}{C_T} \quad ; \quad N_{eq,T} = \frac{L_T}{c_T} \tag{4}$$

3.5. Confidentiality and the illustrative example

The published analysis suppresses the company name, corporate relationships, precise location, personnel details, dates, equipment identifiers, organizational charts, internal forms, actual durations, actual workload totals, and work schedules. Exact source quotations and transformed operational quantities are also omitted because they could permit matching against the original document. The remaining description is limited to the information necessary to understand the measurement problem. No claim of guaranteed anonymization is made.

The numerical example was constructed specifically to demonstrate the equations. Its events and quantities are synthetic and are not perturbed, scaled, or normalized versions of company observations. It is a worked calculation rather than a simulation experiment or an empirical validation dataset. Access to an internship report does not establish permission for public disclosure. The materials supplied did not document a publication-specific authorization or an ethics determination; neither approval nor exemption is asserted in this manuscript.

4. RESULTS AND DISCUSSION

4.1. What the report establishes

The report distinguishes corrective and preventive maintenance and provides an internally traceable calculation for the activities it treats as timed observations. It also recognizes that an interrupted preventive job cannot be represented by its entire opening-to-closing interval. These are useful measurement decisions. The documentary audit does not

reinterpret that recognition as a newly discovered company deficiency. It extends the report's existing caution by examining worker participation, the coverage of supporting work, and the conditions required for a staffing inference.

The report contains varying crew sizes, but it does not provide separate joining and leaving intervals for each technician. Duration multiplied by recorded crew size therefore reconstructs the report's arithmetic under a constant participation assumption.

It does not independently verify each person's active contribution. Likewise, the report's description of responsibilities extends beyond the activities included in the numerical tables. The displayed activity sum should consequently be described as recorded labor for an eligible subset, subject to its timing assumptions. It is not an established total for the maintenance function.

The document also compares the information available for a brief observation period with a longer schedule-based capacity period and explicitly declines to derive headcount from that mismatch. This restraint is warranted. Multiplying the short-period total by the number of days in a week would not solve the problem unless representativeness, capture completeness, and comparable operating conditions were established. Matching calendar units is necessary, but the numerator and denominator must also refer to the same people, work scope, and eligibility rules.

4.2. Missing work and uncertain work time

Two distinct uncertainties remain. First, the quantity attached to a recorded event may be uncertain because active intervals or individual participation are missing. Second, entire duties may fall outside the recorded activity set. Correcting the first uncertainty does not resolve the second. For example, excluding an interrupted job prevents its full open interval from being misclassified as hands-on work, but leaves its actual labor demand unknown. Treating the exclusion as zero would convert a prudent measurement decision into an underestimate.

The direction of error is therefore not fixed. Elapsed intervals and constant crew assumptions can overstate labor for particular recorded jobs. Missing jobs or supporting duties can understate the amount of work over a period. Without validated participation intervals, even the reported subset sum should not automatically be called a lower bound on total true labor. It becomes a defensible lower bound only if the included measurements are themselves valid and represent disjoint contributions. This distinction complements maintenance data quality research that evaluates fitness for a specific analytical purpose (Madhikermi et al., 2016; Conte et al., 2021).

4.3. Synthetic demonstration of the calculation

Table 3 contains five invented events. The fifth has a known job window but no active-time record. It remains unknown. The first four provide enough hypothetical participation detail to calculate direct labor, including interrupted work and a technician who joins for only part of a job. All quantities in this table are illustrative and convey no information about the manufacturing organization.

Table 3. Fully synthetic illustration of elapsed time and direct labor

Event	Work pattern	Elapsed time minutes	Nominal crew	Active participation minutes per worker	Direct labor person-minutes
S1	Continuous repair	12	1	Worker A: 12	12
S2	Two-person repair	18	2	Worker A: 18; B: 18	36
S3	Interrupted prevention	50	1	Worker A: 8 + 12	20
S4	Worker joins part way	30	2	Worker A: 30; B: 10	40
S5	Active time missing	60	1	Unknown	Unknown
Total	Eligible S1–S4	110	—	Separate intervals	108

Note. All events and values are synthetic. The subtotal excludes S5. Elapsed minutes and person-minutes measure different quantities.

The eligible synthetic subtotal is 108 person-minutes: 12 + 36 + 20 + 40. Multiplying each of the four elapsed intervals by its nominal crew size instead produces 158 person-minutes, an overstatement of 50

person-minutes, or 46.3% relative to the valid subtotal. The difference comes from treating the interrupted preventive job as continuous and assuming that both workers remain throughout the partial-team job.

This is an arithmetic demonstration of stated assumptions, not an estimate of bias in the source report or in manufacturing maintenance generally.

Simply summing the four elapsed intervals gives 110 minutes, numerically close to the valid person-time subtotal. That apparent agreement is misleading: it combines unlike quantities and allows different errors to offset one another. The result reinforces the need to check the meaning of each field before comparing totals. The fifth event is excluded from all three subtotals because active labor is unknown. Consequently, 108 person-minutes is not the workload of the complete

synthetic event set. No staff requirement is calculated from this partial total.

4.4. A procedure for deciding what can be reported

Figure 1 sets out the proposed sequence. It separates event-level validity, period coverage, and capacity comparability. Failure at any stage changes the claim that can be made. An interpretable subset can still support a descriptive result, but should not be promoted to a period estimate merely because a capacity figure is available. A valid period estimate can support further scheduling analysis, but cannot establish feasibility without skills, concurrency, and response requirements.

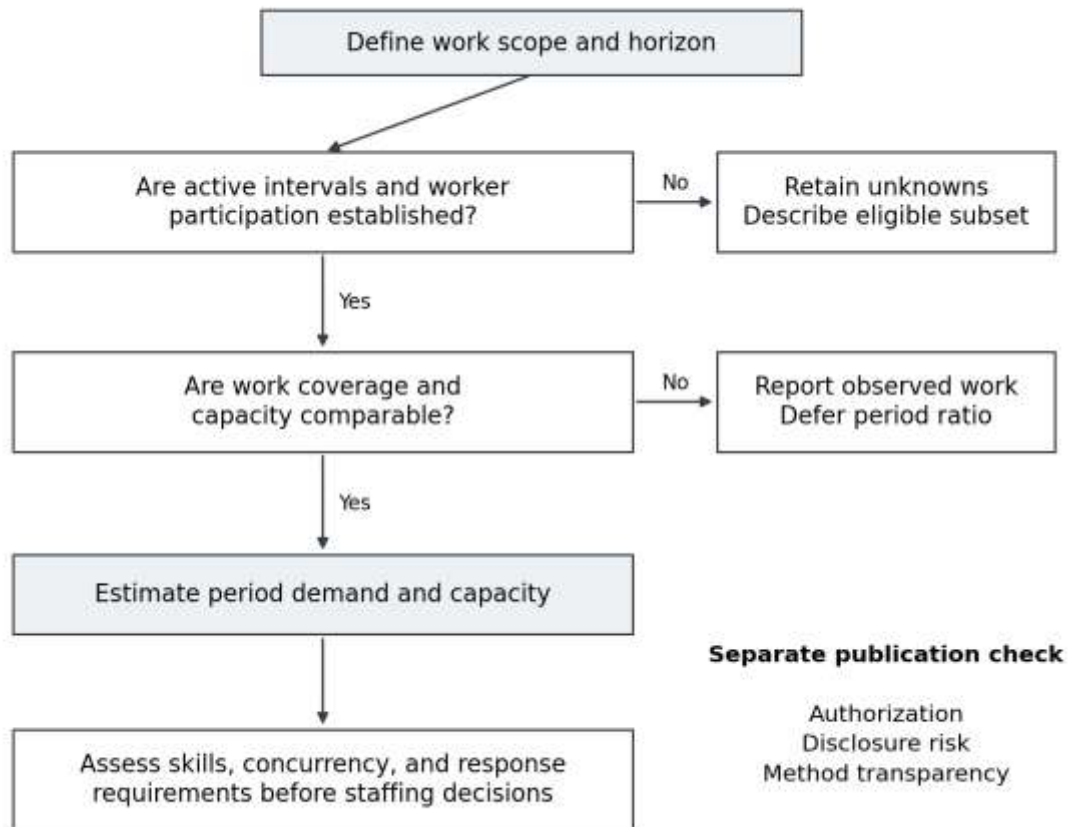


Figure 1. Proposed decision procedure for maintenance labor analysis. Source: methodological synthesis in this article; operational effectiveness has not been evaluated.

The first operational step is to define the work scope. Direct repair, preventive execution, preparation, documentation, assigned waiting, and response readiness should have explicit definitions. The recording form should then capture changes in participation and activity state, including pauses and reassignment. The intended dataset is a sequence of resource

intervals associated with events, rather than a list of job windows alone. A small number of clearly defined fields is preferable to numerous ambiguous categories. Table 4 specifies a proposed schema; it does not describe an implemented system at the case organization.

Table 4. Proposed minimum schema for a prospective workload record

Field group	Required content	Validation or disclosure rule
Internal event key	Unique job identifier and maintenance category.	Check duplicates; replace identifiers in authorized exports.
Worker participation	Pseudonymous worker key and join or leave times.	Check overlap for each worker; keep the identity key restricted.
Activity intervals	Start, stop, resume, and activity state.	Distinguish execution, support, assigned waiting, and readiness.
Work scope	Included duties and exclusion reasons.	Use one classification; retain unknown values explicitly.
Observation coverage	Monitored horizon, missing periods, and capture method.	Do not equate internship attendance with complete observation.
Capacity inputs	Same-horizon roster, breaks, and other unavailability.	Count each exclusion once; reconcile people and periods.
Scheduling context	Required skills, simultaneous staffing, and response targets.	Use after valid labor accounting to assess feasibility.
Provenance and release	Source version, correction log, and disclosure authorization.	Keep an audit trail; publish only the agreed nonidentifying content.

For work performed by several technicians, the participation record should allow different start and finish times. For a single technician

assigned across overlapping jobs, validation should flag any attempt to count the same minute twice as direct execution.

Simultaneous attendance by different technicians can be legitimate and must not be removed as a duplicate. Cross-job allocation rules are therefore essential. A job paused for parts and a technician required to supervise an automated cycle also require different classifications even if neither involves continuous manual action.

At the period level, the analyst should reconcile recorded categories with the declared observation scope, roster, and operational calendars. The absence of a record should have an identifiable meaning: a verified absence of work, an excluded activity, or missing information. Capture completeness cannot be calculated solely from the proportion of completed fields in the jobs that happened to be recorded. A complete-looking table can omit entire tasks. A prospective study should therefore compare the activity log with independently authorized scheduling or observation sources, while acknowledging that these sources may themselves be incomplete.

4.5. Implications for staffing and maintenance management

The documentary evidence does not justify an increase or reduction in staffing. It supports improvement in the information used before such a decision. Once comparable demand and capacity are available, labor equivalents can describe average consumption. Scheduling then requires additional constraints: qualified people must be available together when a job needs a team, response commitments must be met, and relevant work and rest rules must be respected. These requirements are consistent with the distinction between workforce planning and personnel scheduling (Van den Bergh et al., 2013; De Bruecker et al., 2015).

Managers should also distinguish readiness from inactivity. Maintenance services often retain the ability to respond to irregular failures. A low average recorded ratio can reflect omitted work, a quiet period, or deliberately retained response capacity. Conversely, a ratio near full utilization can conceal a service problem if urgent jobs queue or preventive work is repeatedly deferred. The current report contains insufficient evidence to decide among these explanations. Queueing concepts identify the additional questions to ask; they are not a basis for assigning a numerical reserve factor to this case (Little, 1961; Kingman, 1961).

The same caution applies to individual evaluation. Time records should not be used to rank technicians without accounting for task difficulty, assistance provided, assignment rules, and the reliability of attribution. Person-time analysis can support planning, but cannot establish that a worker is fatigued, inattentive, or underperforming. Separate and ethically appropriate methods would be needed for those questions. The proposed procedure is intended to reduce unsupported inferences, not to introduce more intrusive employee monitoring.

4.6. Contribution and limitations

The analytical contribution is an explicit link between three levels of evidence: valid event person time, sufficiently complete period demand, and a feasible staffing decision. The first two can be connected by transparent accounting, but neither guarantees the third. An additional contribution is the separation of internal analysis from external disclosure. The method and synthetic calculation can be made inspectable without publishing the source's operational fingerprint. This arrangement preserves methodological transparency at the cost of limiting independent replication of the private case audit.

Several limitations remain. The evidence consists of a single report selected because it was available, rather than a designed sample of firms or maintenance systems. The audit depends on what the document records; absence of a field is not proof that the underlying organization never records it. The original observation process was not independently verified. The report's arithmetic can be checked internally, but person-level participation, completeness, and observer effects cannot be reconstructed. The narrative literature selection is non-exhaustive and was not independently screened by multiple reviewers. The synthetic example demonstrates calculations only. No operational trial, cost-benefit analysis, validated scoring instrument, or measured performance improvement is reported.

5. CONCLUSION AND RECOMMENDATIONS

Incomplete maintenance activity records can support a useful account of recorded work, provided their unit, coverage, and timing assumptions remain explicit. The supplied report supports such a bounded description and already acknowledges a mismatch between observation and capacity periods. It does not establish complete labor demand or a staffing requirement. The further distinction between event duration and individual participation explains why multiplying elapsed time by nominal crew size may remain conditional even when its arithmetic is correct.

The proposed procedure records active participation and interruptions, preserves unknown quantities, includes support work under a declared scope, and compares demand with capacity for the same workforce and horizon. Its synthetic demonstration shows how overstatement within recorded jobs can coexist with missing demand elsewhere. The resulting recommendation is to improve the evidential basis of workforce decisions before changing headcount. A prospective evaluation should use authorized records across planned and unplanned work, document the coverage of observation, and test whether different recording methods produce consistent person-time estimates. Scheduling feasibility and response performance should then be evaluated separately. Publication must remain subject to documented confidentiality arrangements and the appropriate institutional ethics determination.

6. DECLARATIONS

6.1. Source material and data availability

The analysis uses a privately supplied internship report. Its identifying bibliographic details and operational values are withheld to reduce disclosure risk. The report and underlying company records are not included as public supplementary material. The synthetic example and equations are fully specified in this article. No unrestricted release of the source document or promise of third-party access is made.

6.2. Ethics and confidentiality

No new participants were recruited for this documentary analysis. Publication-specific organizational permission, participant consent where applicable, and an institutional ethics approval or exemption were not documented in the supplied materials. No such approval or exemption is claimed. These matters require an appropriate determination before submission. Suppressing identifiers does not itself replace authorization to use workplace material.

6.3. Authorship, funding and competing interests

Author names and affiliation are provided on the first page. Author contribution statements, funding, and competing interests as confirmation by the submitting author. No additional author, funding award, or absence of competing interests has been inferred from the source document.

6.4. Use of generative artificial intelligence

Generative artificial intelligence assisted with manuscript organization, language drafting, literature discovery, and preparation of the synthetic illustration. No additional field observations or company measurements were generated. The submitting author must review the wording, verify the sources and calculations, and accept responsibility for the final text before submission. This statement records the assistance used and does not assert that author review has already occurred.

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