Multisensor Condition Monitoring and Anomaly Detection in Conveyor Motors: A Retrospective Analysis of Temperature, Vibration-Related Signals and Operating Speed

Lucky Olatunde ODEJIMI[1*], Olusesan OREBANJO[2], Olorunleke AREGBE[1], and Anthony Chijioke ADINGWUPU[3]

[1]Department of Mechanical Engineering, College of Engineering, Igbinedion University Okada, Edo State, Nigeria.
[2]Department of Electrical and Computer Engineering, College of Engineering, Igbinedion University Okada, Edo State, Nigeria.
[3]Department of Mechatronics Engineering, College of Engineering, Igbinedion University Okada, Edo State, Nigeria.
Corresponding Authors Email: odejimi.lucky@iuokada.edu.ng

Direct Research Journal of Engineering and Information Technology

Direct RESEARCH JOURNALS

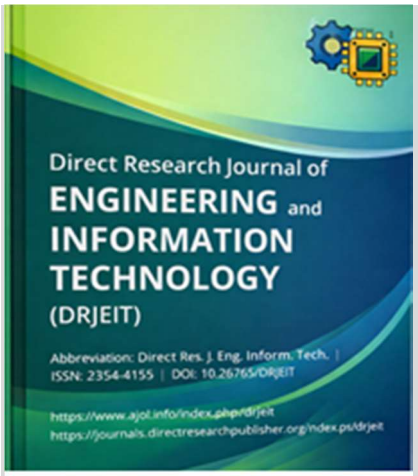
Vol. 14(3), Pp. 137-146, October 2026,
Author(s) retains the copyright of this article
This article is published under the terms of the Creative Commons Attribution License 4.0.
Research Article
ISSN: 2354-4155
https://journals.directresearchpublisher.org/index.php/drjeit; https://www.ajol.info/index.php/drjeit

Received 27 August 2026, Accepted 25 September 2026, Published 29 October

ABSTRACT

Conveyor-motor condition monitoring combines measurements that may reflect thermal state, motion and operating behaviour, but retrospective sensor records can be difficult to compare across sessions. This study analysed archived records from conveyor Motors 3 (M3) and 4 (M4), including normal-operation, recorded-stall and pallet-static/potential-fault sessions, together with separate speed and temperature/vibration-related files. Valid observations were summarised into one-minute windows for descriptive analysis, timestamp alignment and exploratory anomaly detection. The median of one-minute temperature medians was 23.89 °C in the M3 normal record and 31.34 °C in the M3 recorded-stall record. Corresponding summaries were 39.38 °C for M4 recorded stall and 39.71 °C for the M4 pallet-static/potential-fault record. The separate M4 speed file contained 3,781 valid readings, of which 1,415 (37.4%) were zero. The supplied file review indicates that 1,408 zero readings occurred in a sustained end-of-record block, while the remaining seven zero readings were associated with brief dips. These speed patterns do not independently confirm mechanical stalls because synchronised motor-current measurements or independent event logs were unavailable. The separate speed stream was reported at approximately 1 Hz, while the temperature/vibration record was reported at approximately 100 Hz. An Isolation Forest trained on the M3 normal session flagged all windows from the other records, indicating differences between recording sessions rather than verified fault-detection performance. The findings are descriptive and support further session-aware multisensor analysis.

Keywords: *Conveyor Motors; Condition Monitoring; Anomaly Detection; Temperature; Accelerometer Signals; Rotational Speed*



Citation: Odejimi L.O., Orebanjo O., Aragbe O., & Adingwupu A.C. (2026). Multisensor Condition Monitoring and Anomaly Detection in Conveyor Motors: A Retrospective Analysis of Temperature, Vibration-Related Signals and Operating Speed. *Direct Research Journal of Engineering and Information Technology*. 14(3), Pp. 137-146. https://doi.org/10.4314/drjeit.v14i3.11

INTRODUCTION

Conveyor systems support material movement across manufacturing, logistics and processing environments, so unexpected equipment interruptions can affect throughput, maintenance planning and operational reliability. Condition monitoring uses measured equipment behaviour to identify deviations that may warrant investigation, while predictive maintenance attempts to use condition information to guide intervention before failure. Recent reviews describe growing use of data-driven monitoring and machine learning, while also noting barriers involving data quality, model transferability, validation and industrial deployment (Mallioris et al., 2024; Nunes et al., 2023; Polverino et al., 2023; Surucu et al., 2023; Ward et al., 2024). These approaches are most useful when measurements are interpreted in the context of the machine, operating regime and data-acquisition process rather than as isolated model inputs.

Temperature, vibration and other motion-related signals can provide complementary information about rotating machinery. Vibration analysis is widely used to investigate dynamic behaviour and mechanical faults, but signal interpretation depends on sensor selection, mounting, sampling, operating speed and preprocessing (Hassan et al., 2024; Bagri et al., 2024; Qi et al., 2023; Kannan et al., 2024). Reviews of rotating-machinery monitoring also describe the role of feature engineering, health indicators and signal-processing choices in linking measurements to degradation or fault states (Zhou et al., 2022). Multisensor fusion may capture relationships that are not visible in a single channel, although fusion cannot compensate for poorly documented units, unsynchronised streams or uncertain labels (Kibrete et al., 2024; Long et al., 2024).

Machine learning has been applied to condition monitoring, fault diagnosis and prognostics using both conventional and deep-learning approaches (Surucu et al., 2023; Polverino et al., 2023; Qi et al., 2023). However, a high score on a particular dataset is not, by itself, evidence that a model will generalise to a new operating session. Industrial data may be scarce, imbalanced and unevenly labelled, and these issues can distort model development and evaluation (Hakami, 2024; Ward et al., 2024). Anomaly detection adds a related interpretive challenge: an algorithm identifies departures from a reference distribution, but such departures can arise from a genuine fault, a change in load, warm-up, a different motor, a changed sensor configuration or data-quality problems (Panza et al., 2023; Barrish & van Vuuren, 2023; Elía & Pagola, 2025). The Isolation Forest algorithm, for example, isolates observations that are easier to separate from the bulk of the reference data; its score is not a mechanical diagnosis in itself (Liu et al., 2008). Validation design is therefore central to credible condition-monitoring research. Predictive-maintenance studies have highlighted the need to report the data source, preprocessing, evaluation metrics and validation strategy, and to distinguish diagnosis of an observed fault from prognosis of a future event (Polverino et al., 2023; Lei et al., 2018; Susto et al., 2015). Adjacent time windows are often serially dependent, so treating each window as an independent event can overstate the amount of evidence available. More generally, anomaly detection is an application-dependent task in which the definition of an anomaly and the costs of false alarms and missed events shape how performance should be assessed (Chandola et al., 2009; Breunig et al., 2000; Panza et al., 2023). Against this background, the present study retrospectively examines archived M3 and M4 conveyor-motor records to describe temperature, motion-related channels and recorded speed; assess temporal coverage and alignment; and test how an exploratory anomaly detector behaves when trained on one normal-operation record. The study is descriptive and does not assume that the supplied potential-fault label represents a confirmed mechanical failure.

MATERIALS AND METHODS

Study design and data sources

This was a retrospective observational analysis of existing comma-separated-value (CSV) sensor records. The primary records were M3 normal operation, M3 recorded stall, M4 recorded stall and an M4 pallet-static/potential-fault record. Additional files included speed measurements and a temperature/vibration-related record. No new data were collected. The files were treated as distinct recording sessions unless timestamp overlap supported a more direct comparison. The M3 normal record covered 23 June 2021, from 18:08:29 to 23:26:09. The M3 recorded-stall record covered 24 June 2021, from 14:01:43 to 17:13:30. The M4 recorded-stall record covered 24 June 2021, from 15:53:04 to 17:17:02. The M4 pallet-static/potential-fault record covered 23 June 2021, from 18:08:28 to 23:26:01. The available temperature/vibration-related file covered 24 June 2021, from 14:01:42 to 15:12:46. These dates and times describe the records as supplied; they do not by themselves verify the physical cause or severity of any event.

Sensor variables and preprocessing

The sensor files contain temperature (TempC), the Raw channel for rotational speed, and directional accelerometer channels x, y and z. The supplied sensor information identifies an ADXL345 accelerometer for the motion-related channels and a PT100 resistance temperature detector for temperature monitoring. The data provider confirmed that both the Raw channel and the separate speed stream measure rotational speed in revolutions per minute (RPM); x, y and z are measured in gravitational acceleration (g). The sensor assembly was reported to have been mounted close to the motor in a

horizontal position. The reported z-axis mean of approximately 0.987 g is consistent with that axis being aligned with the vertical gravity direction. This is an inference from the static acceleration component rather than a verified mounting record; the x- and y-axis orientations should not be treated as confirmed without original mounting documentation. The separate speed file was reported at approximately 1 Hz, whereas the temperature/vibration record was reported at approximately 100 Hz. These streams therefore have different temporal resolutions and were not treated as interchangeable.

Although both the Raw channel and the separate speed stream are confirmed to report RPM, their absolute scales differ substantially (Raw medians of several thousand RPM versus separate-stream medians near 70 RPM). Possible explanations include different sensing principles, gearing or pulley ratios, encoder resolution, or an undocumented scaling factor. Because the original acquisition documentation did not resolve this discrepancy, the two streams were analysed as related but non-interchangeable indicators of rotational behaviour rather than as numerically equivalent measurements. Records with initialization timestamps from 1970 were excluded in the previous data preparation. For the initial descriptive analysis, valid observations were aggregated into one-minute windows. Median values were used to reduce the influence of short-lived extreme readings. Record-level summaries in this manuscript are the medians of the available one-minute medians, not medians of every raw observation. Missing or incomplete minute windows were not imputed for the descriptive comparisons. Timestamp alignment was treated as a prerequisite for any paired speed–sensor analysis.

Descriptive and temporal analyses

The initial audit documented valid row counts, recording periods and numbers of available one-minute windows. Window-level medians were compared descriptively across records. Time-coverage plots were prepared to visualise differences in duration and overlap. For any inferential comparison, the repeated temporal structure of adjacent windows must be acknowledged; window-level observations within a recording are not independent replicates of separate operating events. Accordingly, differences are interpreted primarily as descriptive contrasts between the available records rather than as general estimates of a fault effect.

Speed alignment

Speed files were inspected for overlap with the M3 and M4 sensor records. Matching was conducted at the timestamp level after aggregating sensor readings to a consistent timestamp resolution. Both the Raw channel and the separate speed stream are measured in RPM, as confirmed by the data provider. The matching was incomplete, so analyses involving speed report the number of matched timestamps. Zero-speed values were retained and examined as recorded. The supplied M4 speed-file review identified 1,415 zero readings among 3,781 valid readings (37.4%); 1,408 were reported to occur in a sustained block near the end of the recording, while the remaining seven occurred in brief dips. Since no synchronised motor-current record or independent event log was available to distinguish a powered mechanical stall from a normal shutdown or a logging artefact, zero-speed episodes were described by their observed pattern and were not treated as confirmed mechanical stalls.

Exploratory anomaly detection

An Isolation Forest was used as an exploratory detector, with the M3 normal-operation one-minute sensor summaries as the reference data. The purpose was to test whether a normal-record baseline could identify departures in the other files. This was not treated as a validated fault classifier: records from different motors and sessions can have different baselines, and an anomaly score indicates deviation from the reference distribution rather than a confirmed mechanical fault. The initial result was evaluated qualitatively against the observed cross-record differences.

Software and analysis environment

Data preparation, one-minute aggregation, descriptive statistics, Spearman correlations and timestamp matching were performed in a standard data-analysis environment. The Isolation Forest was fitted using the scikit-learn implementation with default contamination settings on the M3 normal one-minute feature matrix. Exact package versions and full analysis scripts are available from the corresponding author upon reasonable request.

Ethics and data governance

The analysis used existing equipment sensor records and, based on the supplied information, did not involve human participants or animals. Ethics approval and informed consent were therefore not applicable to the analysis as described; any institutional requirement for a formal determination should be confirmed with the originating institution. The data comprised archived CSV files supplied for this study. Public release depends on the data owner's permission; where public sharing is not authorised, access may be requested from the corresponding author subject to the owner's approval.

RESULTS

Data coverage and completeness

The five sensor records differed in duration and data volume (Table 1). After exclusion of initialization rows with

Table 1: Recording coverage after exclusion of initialization rows.

Record	Start	End	Valid rows	Unique second timestamps	Minute windows
M3 normal	2021-06-23 18:08:29	2021-06-23 23:26:09	1,745,677	18,165	317
M3 recorded stall	2021-06-24 14:01:43	2021-06-24 17:13:30	923,020	9,646	178
M4 recorded stall	2021-06-24 15:53:04	2021-06-24 17:17:02	404,003	4,182	77
M4 potential-fault/static	2021-06-23 18:08:28	2021-06-23 23:26:01	1,763,974	18,410	317
M4 temperature/vibration	2021-06-24 14:01:42	2021-06-24 15:12:46	376,617	3,960	70

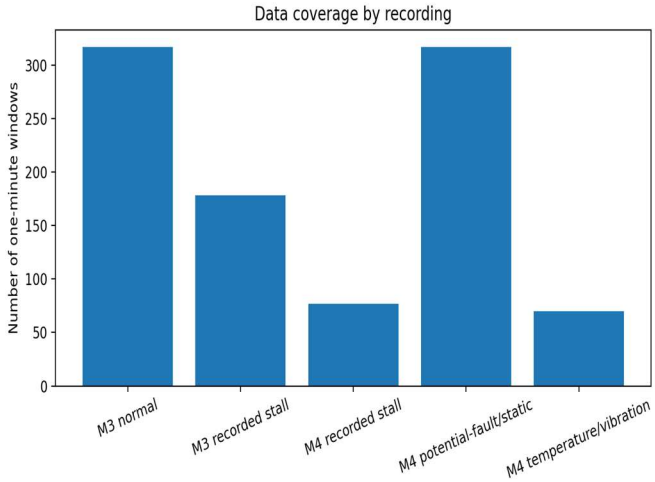


Figure 1: Number of one-minute windows available in each sensor record.

timestamps from 1970, the M3 normal-operation record contained 1,745,677 valid rows across 317 one-minute windows. The M4 pallet-static/potential-fault record contained 1,763,974 valid rows across 317 windows. The M3 recorded-stall record contained 923,020 rows across 178 windows, while the M4 recorded-stall record contained 404,003 rows across 77 windows. The additional M4 temperature/vibration record contained 376,617 rows across 70 windows. These counts describe the available files and should not be interpreted as independent experimental replicates. Figure 1 shows the number of one-minute windows available for each record. Similar coverage duration for the M3 normal and M4 pallet-static/potential-fault files allow descriptive temporal comparison, but the record labels and operating conditions are not equivalent or fully verified.

Descriptive sensor statistics

The median of one-minute temperature medians was 23.89 °C for M3 normal operation and 31.34 °C for the M3 recorded-stall session. Corresponding values in the M4 recorded-stall and pallet-static/potential-fault records were 39.38 °C and 39.71 °C. The median of one-minute RPM medians (Raw channel) was 9,176.03 RPM in M3 normal operation and 6,596.43 RPM in the M3 recorded-stall session; corresponding values were 4,691.54 RPM for M4 recorded stall, 4,628.57 RPM for M4 potential-fault/static, and 4,733.81 RPM for the additional M4 temperature/vibration record. As noted in Section 2.2, these Raw-channel values differ in absolute scale from the separate speed stream (medians near 70 RPM). The x, y and z channels are measured in g. These summaries describe the recorded sessions and do not establish condition-specific thresholds (Table 2). Directional-channel summaries were broadly similar within the M4 records, while the M3 normal and recorded-stall records showed modest differences. These are descriptive comparisons of window medians; because each record is a session rather than an independent replicate, they do not establish condition-specific thresholds (Figure 2 and Figure 3).

Table 2: Median (interquartile range) of one-minute medians for each recorded sensor channel. Temperature is in °C, RPM is the Raw-channel value in revolutions per minute, and x, y and z are in g.

Record	TempC	RPM (Raw)	x	y	z
M3 normal	23.890 [23.540, 23.980]	9176.030 [9140.190, 9320.750]	0.030 [0.030, 0.030]	0.010 [0.010, 0.010]	0.990 [0.990, 0.990]
M3 recorded stall	31.340 [31.250, 31.430]	6596.430 [6569.580, 6623.380]	0.020 [0.020, 0.020]	0.010 [0.010, 0.010]	0.990 [0.990, 0.990]
M4 recorded stall	39.380 [37.150, 40.810]	4691.540 [4422.530, 5147.930]	0.030 [0.030, 0.030]	0.060 [0.060, 0.060]	0.980 [0.980, 1.010]
M4 potential-fault/static	39.710 [39.490, 39.820]	4628.570 [4607.700, 4670.490]	0.030 [0.030, 0.030]	0.050 [0.050, 0.050]	0.980 [0.980, 0.980]
M4 temperature/vibration	39.160 [38.950, 39.270]	4733.810 [4712.640, 4776.330]	0.030 [0.030, 0.030]	0.060 [0.060, 0.060]	0.990 [0.990, 0.990]

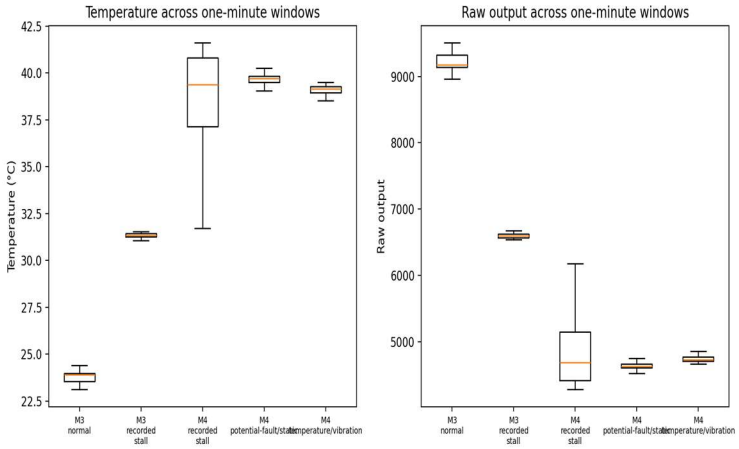


Figure 2: Distribution of one-minute temperature and RPM medians by recording. Boxes show the interquartile range and median; extreme points are hidden for readability.

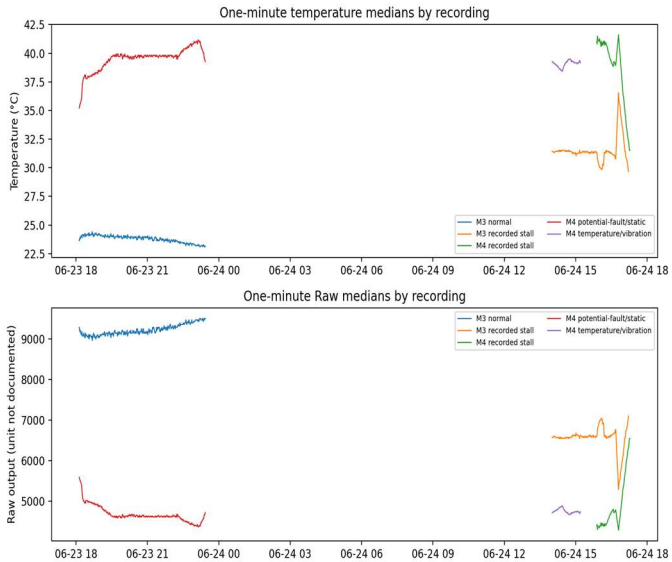


Figure 3: One-minute time series of temperature and RPM. Records are shown on their actual date/time axes and should not be read as a continuous common experiment.

Temporal trends within records

Spearman rank correlations between sequential one-minute windows and channel values described monotonic within-record trends (Table 3). In the M3 normal record, temperature declined strongly across the session (ρ =

Table 3: Spearman correlations between sequential one-minute window index and channel values. P-values are nominal and do not account for serial dependence.

Record	Channel	Windows	Spearman rho vs time	p value
M3 normal	TempC	317	−0.907	<0.001
M3 normal	RPM	317	0.907	<0.001
M3 normal	x	317	—	—
M3 normal	y	317	—	—
M3 normal	z	317	−0.097	0.084
M3 recorded stall	TempC	178	−0.246	<0.001
M3 recorded stall	RPM	178	0.246	<0.001
M3 recorded stall	x	178	0.270	<0.001
M3 recorded stall	y	178	0.006	0.938
M3 recorded stall	z	178	0.586	<0.001
M4 recorded stall	TempC	77	−0.899	<0.001
M4 recorded stall	RPM	77	0.899	<0.001
M4 recorded stall	x	77	—	—
M4 recorded stall	y	77	—	—
M4 recorded stall	z	77	0.853	<0.001
M4 potential-fault/static	TempC	317	0.810	<0.001
M4 potential-fault/static	RPM	317	−0.810	<0.001
M4 potential-fault/static	x	317	—	—
M4 potential-fault/static	y	317	0.716	<0.001
M4 potential-fault/static	z	317	−0.330	<0.001
M4 temperature/vibration	TempC	70	0.485	<0.001
M4 temperature/vibration	RPM	70	−0.485	<0.001
M4 temperature/vibration	x	70	—	—
M4 temperature/vibration	y	70	—	—
M4 temperature/vibration	z	70	—	—

Table 4: Summary of available speed records (separate stream).

Record	Rows	Start	End	Median	Q1	Q3	Min	Max	Zero (%)
M3 speed	3,865	2021-06-24 14:01:42	2021-06-24 15:12:45	72.670	71.470	73.800	66.670	78.000	0.000
M4 speed	3,781	2021-06-24 15:53:04	2021-06-24 17:12:48	71.930	0.000	73.730	0.000	79.120	37.424

−0.907), while RPM increased (ρ = 0.907). In the M3 recorded-stall record, temperature declined more modestly (ρ = −0.246) while RPM increased (ρ = 0.246). Some accelerometer channels also varied over time, including the z channel in the M3 recorded-stall session (ρ = 0.586). These patterns may reflect changing thermal or operating state, but cannot be attributed specifically to a fault without session context and independent event replication. The nominal p-values are presented only as descriptive trend indicators. Adjacent windows are serially dependent, and the number of windows does not represent an equivalent number of independent events.

Operating-speed records and alignment

The separate M3 speed file contained 3,865 readings from 24 June 2021 14:01:42 to 15:12:45; its median was 72.67 RPM (interquartile range [IQR] 71.47–73.80), with no zero readings. After exclusion of initialization records dated 1970, the separate M4 speed file contained 3,781 valid readings from 15:53:04 to 17:12:48; its median was 71.93 RPM (IQR 0–73.73), and 1,415 readings (37.4%) were zero. The supplied file review indicates that 1,408 zero readings were concentrated in a sustained end-of-record block, reported as approximately 23 minutes, while the remaining seven zero readings occurred in brief dips. The sustained block is consistent with a shutdown period, but its cause has not been independently verified. Brief zero-speed readings also cannot establish a mechanical stall without evidence that the motor remained energised. Both the Raw channel and the separate speed file measure rotational speed in RPM; however, as noted earlier, their absolute scales differ and they should not be treated as numerically interchangeable. The separate speed file was reported at approximately 1 Hz, while the temperature/vibration record was reported at approximately 100 Hz; their differing temporal resolutions should be considered when interpreting timestamp alignment and short-duration events (Table 4 and Figure 4). Timestamp matching produced 3,616 paired second-level timestamps for the M3 recorded-stall sensor and separate speed records and 3,549 for M4. Spearman associations in matched observations were weak for most M3 channels. For M4, the separate RPM stream was positively associated with temperature (ρ = 0.492) and negatively associated with the Raw RPM channel (ρ = −0.492); the z channel showed a strong negative association (ρ = −0.797).

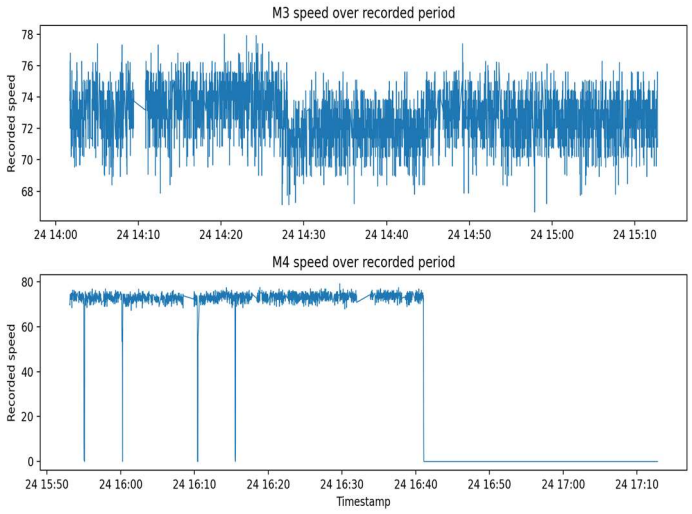


Figure 4: Separate RPM streams for M3 and M4.

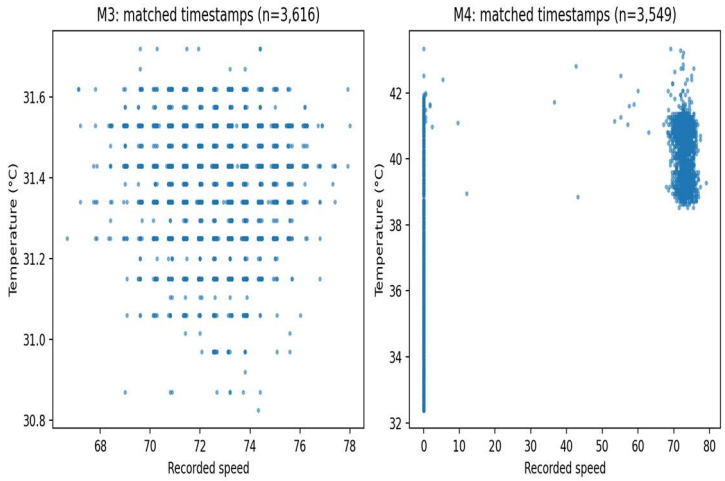


Figure 5: Temperature and separate RPM stream at matched timestamps. Points are temporally autocorrelated; the plot describes association and does not establish a causal effect.

These associations are descriptive and do not establish causal relationships (Figure 5).

Exploratory anomaly detection

An exploratory Isolation Forest fitted to M3 normal-operation one-minute summaries flagged all windows in the other available records as anomalous. This outcome indicates that the other records differed substantially from the single-record baseline under the selected features and settings. It does not show that every flagged window was faulty, nor does it provide a validated sensitivity, specificity, false-alarm rate or early-warning capability. The result is consistent with the possibility that differences between records and operating sessions dominate the model output.

Summary of results

M3 normal and recorded-stall sessions differed in temperature and RPM summaries, but the comparison is confounded by separate recording sessions and dates.
The two M4 records had similar central temperature and RPM summaries despite different labels; the pallet-static/potential-fault label is not confirmed as a diagnosed failure. Temperature and RPM showed opposing monotonic trends in the M3 records, particularly in the normal-operation session. The separate M4 speed file contained 37.4% zero readings. The supplied file review indicates that most were concentrated in a sustained end-

of-record block, with seven remaining zero readings reported in brief dips. The sustained block is consistent with an end-of-run shutdown, but neither the shutdown state nor the cause of the brief dips was independently verified. Synchronous motor-current data or independent event logs would be needed to distinguish normal shutdown from a powered mechanical stall. The exploratory anomaly detector flagged every non-baseline record, supporting further validation rather than a claim of successful fault detection.

DISCUSSION

This study found clear differences between the two available M3 sessions, with median one-minute temperature summaries of 23.89 °C during the record labelled normal operation and 31.34 °C during the recorded-stall session. The difference is a useful descriptive observation, but it cannot be attributed specifically to stall because each operating state is represented by a single session collected on a different date. This distinction matters in condition-monitoring research: reviews repeatedly identify data representativeness, operating-condition variability and real-world validation as important constraints on machine-learning performance (Polverino et al., 2023; Surucu et al., 2023; Mallioris et al., 2024; Ward et al., 2024). The results therefore agree with the broader literature on the potential value of sensor-based monitoring, while illustrating why observed separation in a small archive should not be equated with a transferable diagnostic rule.

The M4 records provide a second caution. The recorded-stall session and the pallet-static/potential-fault record had similar central temperature summaries (39.38 °C and 39.71 °C) and similar RPM summaries, despite different supplied descriptions. This does not prove that the two operating states are equivalent; instead, it shows that the current labels and available channels do not support a simple interpretation in which temperature or RPM alone separates the records. Reviews of vibration and rotating-machinery diagnosis emphasise that fault signatures depend on fault type, measurement setup, machine state and signal processing (Hassan et al., 2024; Bagri et al., 2024; Kannan et al., 2024; Zhou et al., 2022). The M4 potential-fault description should consequently remain provisional unless it can be corroborated by maintenance documentation or an independently recorded event.

Within-record temporal analysis showed a strong decline in temperature and a rise in RPM during the M3 normal session, with a weaker opposing trend in the M3 recorded-stall session. The same directional pattern in two channels does not establish a causal or physical relationship because both speed channels are confirmed to measure rotational speed in RPM (albeit on different absolute scales). Possible explanations include thermal settling, changes in load or operating regime, sensor response, or a shared time trend; the present data cannot distinguish among them. Recent work on vibration sensing and health-indicator construction stresses the importance of measurement context and interpretable features before a signal is treated as evidence of degradation (Hassan et al., 2024; Zhou et al., 2022; Bagri et al., 2024). In addition, consecutive one-minute windows are not independent experimental events. Nominal trend p-values should therefore be interpreted cautiously, and the strength and direction of the observed patterns are more informative here than conventional significance labels.

The matched M4 observations showed a moderate positive association between the separate speed stream and temperature (Spearman $\rho = 0.492$), a negative association between the separate speed stream and the Raw RPM channel ($\rho = -0.492$), and a strong negative association between speed and the z channel ($\rho = -0.797$). These are within-session associations, not evidence that speed caused the other channels to change. Shared time trends, operating-state transitions and zero-valued speed readings could all influence the associations. The file-level review indicates that most M4 zero readings were concentrated in a sustained end-of-record block, while seven occurred in brief dips. The long block is consistent with a shutdown period, whereas the brief dips may represent transient speed interruptions; neither interpretation is confirmed from speed alone. A mechanical stall must be distinguished from a normal stop by checking whether current remains present while speed is zero. Because synchronised current measurements were not available, the brief dips are not labelled as verified stalls. The difference in sampling rates—approximately 1 Hz for the separate speed stream and approximately 100 Hz for the temperature/vibration record—also needs to be considered when interpreting alignment and short-duration events. Multisensor approaches are increasingly studied for machine diagnosis, but their value depends on synchronisation, sensor provenance and a defensible interpretation of each signal (Kibrete et al., 2024; Long et al., 2024; Mallioris et al., 2024).

The broader literature supports combining complementary measurements where each channel is technically understood and correctly aligned (Kibrete et al., 2024; Long et al., 2024; Hassan et al., 2024). The present archive is a useful starting point for that approach, but it does not yet establish the benefit of multisensor fusion over single-channel monitoring because the available sessions are limited and the sensor definitions are incomplete. A stronger next study would include multiple independently recorded normal and fault events, confirmed onset times, operating-load and ambient-context information, sensor mounting and calibration records, and a test design that holds out complete sessions or events. Reviews of prognostics and predictive maintenance similarly emphasise that evaluation should reflect the intended deployment setting and that diagnostic classification must be distinguished from forecasting a future failure (Lei et al., 2018; Susto et al., 2015; Polverino

et al., 2023; Hakami, 2024). The Isolation Forest fitted to the M3 normal-operation windows flagged all windows in the other records as anomalous. This should not be interpreted as 100% fault-detection performance. Isolation Forest detects observations that differ from its reference distribution, and the reference distribution here came from one motor session only (Liu et al., 2008). The result is therefore consistent with a baseline that does not transfer across sessions, motors or operating regimes. Industrial anomaly-detection reviews emphasise that anomalies are context-dependent and that useful evaluation requires representative test data and meaningful labels (Panza et al., 2023; Barrish & van Vuuren, 2023; Elía & Pagola, 2025). Without independently labelled events, the present study cannot estimate sensitivity, specificity, precision, false-alarm rate or warning lead time. This outcome is best treated as a diagnostic lesson about baseline transferability, not as evidence of successful automated detection.

The practical contribution is methodological: archived industrial data can support useful exploratory analysis, but model claims must be limited by the design and quality of the evidence. The current findings justify further investigation of thermal trends, RPM-channel behaviour and speed–sensor alignment; they do not justify deployment of a threshold or classifier for maintenance decisions. Future work should verify the physical units and acquisition conventions (including the absolute-scale difference between the Raw and separate speed streams), confirm the M4 event label, establish the timing of any stall onset, and assess performance on multiple independent sessions. This aligns with research calling for more transparent real-data evaluation, explicit handling of scarcity and imbalance, and validation methods that better represent operational use (Hakami, 2024; Ward et al., 2024; Mallioris et al., 2024; Polverino et al., 2023).

Limitations

The analysis describes the available recording sessions using one-minute summaries, timestamp-matched speed measurements and exploratory anomaly detection. The records represent distinct sessions and supplied operating-state labels; results are therefore presented as descriptive evidence from this archive. Both the Raw channel and the separate speed stream are confirmed to measure RPM, yet their absolute scales differ substantially and the reason for the discrepancy was not resolved by the available documentation. The x, y and z accelerometer channels are measured in g. The reported z-axis mean of approximately 0.987 g is consistent with the axis being aligned with gravity, but this remains an inference; the x- and y-axis orientations were not independently verified. The separate speed file was reported at approximately 1 Hz and the temperature/vibration record at approximately 100 Hz. The M4 speed file contained a sustained end-of-record zero-speed block and seven additional zero readings in brief dips. Without synchronized current data or independent event logs, these patterns are interpreted as recorded zero-speed periods rather than confirmed mechanical stalls. Each operating condition is represented by only one or two sessions, so session-level confounding cannot be separated from condition effects.

Conclusion

This retrospective analysis identified descriptive differences and temporal patterns in archived conveyor-motor records. The M3 normal and recorded-stall sessions differed in their temperature and RPM summaries, while the two M4 records had similar central summaries despite different supplied labels. The separate M4 speed record contained a sustained end-of-record period of zero readings and seven additional zero readings associated with brief dips, according to the supplied file review. These patterns may guide follow-up investigation, but speed alone cannot establish whether a brief event was a mechanical stall or whether a prolonged zero-speed period reflected a normal shutdown. Synchronous motor-current data and independent event records would be required to confirm stall events. The z-axis mean was consistent with the vertical gravity direction, although the full accelerometer mounting orientation was not documented. An Isolation Forest trained on a single normal session flagged all other records, indicating that the reference profile differed from the other sessions rather than demonstrating validated fault detection. The findings provide a basis for further session-aware analysis of temperature, vibration-related channels and rotational speed.

Declarations

Funding: The authors received no specific funding for this research from any public, commercial, or not-for-profit funding agency.

Conflicts of Interest: The authors declare that they have no conflicts of interest that could have influenced the conduct, analysis, or reporting of this study.

Author Contributions: The first author conceived and designed the study, conducted the research, analysed and interpreted the data, and prepared the original manuscript. The other authors reviewed the manuscript, provided corrections and intellectual input, and approved the final version for submission. All authors read and approved the final manuscript.

Data Availability: The data analysed in this study comprise archived CSV files supplied for the research. These data are available from the corresponding author upon reasonable request, subject to the data owner's permission and any applicable data-sharing restrictions.

Ethics Approval: The study analysed existing equipment sensor records and involved neither human participants nor animals. Accordingly, ethics approval and informed consent were not applicable, subject to any formal determination required by the originating institution.

REFERENCES

Bagri, I., Tahiry, K., Hraiba, A., Touil, A., & Mousrij, A. (2024). Vibration signal analysis for intelligent rotating machinery diagnosis and prognosis: A comprehensive systematic literature review. Vibration, 7(4), 1013–1062. https://doi.org/10.3390/vibration7040054

Barrish, D., & van Vuuren, J. (2023). A taxonomy of univariate anomaly detection algorithms for predictive maintenance. The South African Journal of Industrial Engineering, 34(3), 28–42. https://doi.org/10.7166/34-3-2943

Breunig, M. M., Kriegel, H.-P., Ng, R. T., & Sander, J. (2000). LOF: Identifying density-based local outliers. In Proceedings of the 2000 ACM SIGMOD International Conference on Management of Data (pp. 93–104). Association for Computing Machinery. https://doi.org/10.1145/342009.335388

Chandola, V., Banerjee, A., & Kumar, V. (2009). Anomaly detection: A survey. ACM Computing Surveys, 41(3), Article 15. https://doi.org/10.1145/1541880.1541882

Elía, I., & Pagola, M. (2025). Anomaly detection in smart-manufacturing era: A review. Engineering Applications of Artificial Intelligence, 139, Article 109578. https://doi.org/10.1016/j.engappai.2024.109578

Hakami, A. (2024). Strategies for overcoming data scarcity, imbalance, and feature selection challenges in machine learning models for predictive maintenance. Scientific Reports, 14, Article 9645. https://doi.org/10.1038/s41598-024-59958-9

Hassan, I. U., Panduru, K., & Walsh, J. (2024). An in-depth study of vibration sensors for condition monitoring. Sensors, 24(3), Article 740. https://doi.org/10.3390/s24030740

Kannan, V., Zhang, T., & Li, H. (2024). A review of the intelligent condition monitoring of rolling element bearings. Machines, 12(7), Article 484. https://doi.org/10.3390/machines12070484

Kibrete, F., Woldemichael, D. E., & Gebremedhin, H. S. (2024). Multi-sensor data fusion in intelligent fault diagnosis of rotating machines: A comprehensive review. Measurement, 232, Article 114658. https://doi.org/10.1016/j.measurement.2024.114658

Lei, Y., Li, N., Guo, L., Li, N., Yan, T., & Lin, J. (2018). Machinery health prognostics: A systematic review from data acquisition to remaining useful life prediction. Mechanical Systems and Signal Processing, 104, 799–834. https://doi.org/10.1016/j.ymssp.2017.11.016

Liu, F. T., Ting, K. M., & Zhou, Z.-H. (2008). Isolation forest. In 2008 Eighth IEEE International Conference on Data Mining (pp. 413–422). IEEE. https://doi.org/10.1109/ICDM.2008.17

Long, Z., Guo, J., Ma, X., Wu, G., Rao, Z., Zhang, X., & Xu, Z. (2024). Motor fault diagnosis based on multisensor-driven visual information fusion. ISA Transactions, 155, 524–535. https://doi.org/10.1016/j.isatra.2024.09.024

Mallioris, P., Aivazidou, E., & Bechtsis, D. (2024). Predictive maintenance in Industry 4.0: A systematic multi-sector mapping. CIRP Journal of Manufacturing Science and Technology, 50, 80–103. https://doi.org/10.1016/j.cirpj.2024.02.003

Nunes, P., Santos, J., & Rocha, E. (2023). Challenges in predictive maintenance—A review. CIRP Journal of Manufacturing Science and Technology, 40, 53–67. https://doi.org/10.1016/j.cirpj.2022.11.004

Panza, M. A., Pota, M., & Esposito, M. (2023). Anomaly detection methods for industrial applications: A comparative study. Electronics, 12(18), Article 3971. https://doi.org/10.3390/electronics12183971

Polverino, L., Abbate, R., Manco, P., Perfetto, D., Caputo, F., Macchiaroli, R., & Caterino, M. (2023). Machine learning for prognostics and health management of industrial mechanical systems and equipment: A systematic literature review. International Journal of Engineering Business Management, 15, 1–20. https://doi.org/10.1177/18479790231186848

Qi, R., Zhang, J., & Spencer, K. (2023). A review on data-driven condition monitoring of industrial equipment. Algorithms, 16(1), Article 9. https://doi.org/10.3390/a16010009

Surucu, O., Gadsden, S. A., & Yawney, J. (2023). Condition monitoring using machine learning: A review of theory, applications, and recent advances. Expert Systems with Applications, 221, Article 119738. https://doi.org/10.1016/j.eswa.2023.119738

Susto, G. A., Schirru, A., Pampuri, S., McLoone, S., & Beghi, A. (2015). Machine learning for predictive maintenance: A multiple classifier approach. IEEE Transactions on Industrial Informatics, 11(3), 812–820. https://doi.org/10.1109/TII.2014.2349359

Ward, T., Jenab, K., Ortega-Moody, J., & Staub, S. (2024). A comprehensive review of machine learning techniques for condition-based maintenance. International Journal of Prognostics and Health Management, 15(2). https://doi.org/10.36001/ijphm.2024.v15i2.3850

Zhou, H., Huang, X., Wen, G., Lei, Z., Dong, S., Zhang, P., & Chen, X. (2022). Construction of health indicators for condition monitoring of rotating machinery: A review of the research. Expert Systems with Applications, 203, Article 117297. https://doi.org/10.1016/j.eswa.2022.117297