

Multivariate Data-Based Anomaly Characterisation of a Potential Pallet-Associated Event in a Manufacturing Conveyor System

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ABSTRACT

Manufacturing conveyor disturbances may not be adequately characterised by single-sensor thresholds because operating changes can appear across multiple sensor channels. This study examined whether a recorded M4 pallet-static event contained multivariate sensor patterns that differed from a recorded M4 stall condition. The analysis used temperature (TempC), raw sensor output (Raw), three directional components (x, y and z), and a resultant magnitude derived from the directional components. Following timestamp reconstruction and data screening, observations were aggregated into one-minute medians. Descriptive statistics, Pearson correlation, principal component analysis (PCA), Isolation Forest and two-sided Mann–Whitney U tests with rank-biserial effect sizes were used for exploratory analysis. The pallet-static record yielded 317 one-minute windows, of which 16 (5.05%) were flagged as candidate anomalies under a 5% Isolation Forest contamination setting. Temperature and Raw output were strongly inversely correlated ($r = -0.9991$), while comparisons with the M4 stall record indicated distributional differences in y, z and resultant magnitude but not in temperature or Raw output, according to the reported unadjusted tests. PCA showed partial separation between the event groups. These findings suggest that directional channels may add descriptive information beyond temperature and Raw output alone. However, the source records do not independently verify a pallet-caused mechanical fault, and the statistical comparisons require confirmation in light of temporal dependence and multiple testing. The framework should therefore be treated as exploratory and validated against independently labelled events before operational deployment.

Keywords: Manufacturing conveyor; anomaly detection; predictive maintenance; multivariate recorded data; Isolation Forest; pallet-associated event; condition monitoring; principal component analysis



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INTRODUCTION

Manufacturing conveyor systems are essential elements of automated material-handling and production environments because they support the continuous movement of components, products, and loads between process stages. Their reliable operation is therefore closely connected with production continuity, equipment availability, and maintenance efficiency. In modern manufacturing, condition-monitoring strategies increasingly use recorded data to identify deviations from expected machine behaviour before they develop into more disruptive events. Predictive maintenance has consequently become an important data-driven maintenance strategy for intelligent manufacturing, although successful implementation still depends on data quality, appropriate analytical methods, and integration with maintenance practice (Hoffmann & Lasch, 2025; Ramzan & Reforgiato Recupero, 2025). Recent Industry 4.0 research similarly identifies vibration, temperature, pressure, and other sensor signals as important sources for condition assessment and predictive maintenance (Cools et al., 2025).

The increasing availability of inexpensive sensor variables has made it possible to monitor manufacturing equipment through multiple simultaneously sensor variables rather than relying on a single threshold. This development is important because industrial equipment is characterized by interacting physical processes, and a disturbance may appear differently across temperature, motion, vibration, load, or control signals. Recent work on multivariate time-series anomaly detection emphasizes that the relationships among simultaneously measured variables can contain information that is lost when each signal is analysed independently (Guan et al., 2024; Kang & Kang, 2024). Correia et al. (2024) further note that multivariate anomaly detection in engineering processes involves challenges associated with dimensionality, temporal dependence, threshold selection, and realistic evaluation. These challenges are directly relevant to conveyor condition monitoring, where sensor responses can change together during loading, acceleration, stopping, or abnormal resistance events.

Anomaly detection is particularly relevant when confirmed fault labels are limited. In many industrial settings, normal operating records are much easier to collect than large numbers of mechanically verified failures. Unsupervised or semi-supervised approaches can therefore provide a practical first stage for identifying observations that differ from the dominant operating pattern. López et al. (2023) demonstrated that multivariate anomaly detection can be combined with false-positive mitigation in predictive-maintenance applications, emphasizing that raw anomaly flags should not automatically be treated as confirmed faults. More recent studies have continued to investigate unsupervised approaches for industrial recorded data, including adaptive models and representation-learning methods (Rodríguez-

Ossorio et al., 2025; Yang et al., 2024). The problem is becoming more complex as manufacturing systems generate increasingly high-dimensional and non-stationary time-series data. Orabi et al. (2024) developed an adaptive adversarial Transformer approach specifically to capture temporal patterns in high-dimensional, multivariate, non-stationary manufacturing data. Kang and Kang (2024) similarly addressed the challenge of learning temporal dependencies and inter-variable relationships in multivariate sensor streams through an attention-based architecture. Guan et al. (2024) reported that complex physical equipment may require many sensor variables and that spatial and temporal dependencies can complicate anomaly identification. These studies illustrate the technological direction of the field, but they also indicate that anomaly detection does not necessarily require the most computationally complex model for every industrial application.

For smaller experimental manufacturing systems, interpretable statistical and machine-learning techniques can be valuable because they can reveal which measured variables are associated with an abnormal event. Feature selection is especially relevant because redundant or weakly informative variables can complicate model interpretation. Li et al. (2024) showed that feature selection can improve industrial multivariate time-series anomaly detection and emphasized the importance of accounting for chronological relationships and cross-variable interactions. Their work used an industrial vertical-roller-mill dataset and demonstrated that selecting representative features can improve downstream anomaly-detection performance. This supports the use of explicit variable-level analysis alongside a multivariate detector in the present conveyor study.

Another important issue is the evaluation of anomaly-detection systems. A detector may identify unusual observations successfully while still producing false alarms, especially when operating conditions vary. López et al. (2023) specifically addressed false-positive mitigation, while Sørbo and Ruocco (2024) showed that time-series anomaly-detection evaluation is complicated by differences in definitions, thresholds, event boundaries, and metrics. Cools et al. (2025), in a benchmarking study for Industry 4.0, likewise emphasized that anomaly-detection methods should be evaluated in relation to the characteristics of the application rather than assumed to perform equally across industrial datasets. These observations support the present study's decision to report statistical comparisons, effect sizes, anomaly scores, and multivariate projections instead of relying on a single classification accuracy measure.

Conveyor systems provide a particularly useful setting for this type of investigation because abnormal loading can produce simultaneous changes in several operating variables. A pallet that interacts differently with a conveyor may alter resistance, motion, vibration, or motor-related

behaviour. However, sensor changes alone cannot establish physical causation unless the event is independently verified. This distinction is essential in the present study. The supplied M4 dataset is associated with a pallet-static or potential-fault event, but the available records do not provide an independent mechanical inspection confirming that the pallet caused the observed sensor changes. Accordingly, the present work investigates a potential pallet-associated anomaly signature rather than claiming a confirmed pallet-induced mechanical failure. Recent conveyor-related research demonstrates that data-driven monitoring can be applied to conveyor-belt systems. Gunckel et al. (2025) investigated machine-learning-based failure prediction using operational and control-area information. Separately, Wang and Liu (2024) developed a graph-attention and Transformer approach for multivariate time-series anomaly detection, providing methodological context rather than conveyor-specific evidence. The present study differs by focusing on a compact multivariate sensor-data series and unusual windows associated with a potential pallet-static event.

The choice of an unsupervised anomaly detector is also motivated by the structure of the available evidence. A supervised classifier requires sufficiently representative and independently verified labels for each condition, whereas the present potential-fault event is not accompanied by a comprehensive set of confirmed pallet-induced failure labels. Isolation Forest provides a computationally relatively lightweight mechanism for identifying observations that are unusual within a multidimensional feature space. The method is consistent with the broader use of unsupervised approaches in industrial anomaly detection, although recent literature also includes more complex autoencoder, graph, and Transformer-based approaches (Guan et al., 2024; Orabi et al., 2024; Rodríguez-Ossorio et al., 2025). The present study therefore treats Isolation Forest as an exploratory detector rather than as a definitive diagnostic model. Multivariate analysis is also justified by the possibility that abnormal behaviour may not be extreme in any single sensor. An event can be characterized by a combination of moderate changes occurring simultaneously across several variables. The present study adopts a simpler but transparent approach by combining temperature, Raw output, x, y, z, and a mathematically derived resultant magnitude. Correlation analysis and principal component analysis are then used to examine the relationships and overall structure of these variables.

The resultant magnitude is a compact representation of the three directional components, calculated as $R = \sqrt{x^2 + y^2 + z^2}$. Because it is mathematically derived rather than independently measured, it is not an independent source of evidence. Analyses including the resultant should be interpreted cautiously, and sensitivity analyses excluding it are needed. Temporal processing is another central consideration. Industrial sensor observations are not

independent measurements in the conventional statistical sense; successive observations are linked by machine operating state and process dynamics. Correia et al. (2024) describe temporal dependence as a central issue in online multivariate anomaly detection, while Kang and Kang (2024) explicitly model temporal and inter-variable dependencies. The present study therefore reconstructs time stamps and aggregates observations into one-minute analytical windows. Median aggregation is used to reduce the influence of isolated extreme readings while preserving the evolution of the event. This produces an interpretable event-level representation suitable for exploratory statistical and machine-learning analysis.

At the same time, aggregation introduces a methodological trade-off. Very short transient events may be diluted when observations are summarized over a minute. This limitation is relevant to pallet interactions because a mechanical contact or resistance event could occur over a much shorter interval than the analytical window. Recent manufacturing research has consequently investigated cycle-aware and sub-cycle approaches for anomaly detection and predictive maintenance (Zubieta et al., 2025). The present one-minute analysis should therefore be regarded as a first-level event characterization, with higher-frequency analysis recommended for future work if raw sensor timing is available.

PCA provides an additional exploratory perspective because it can show whether the multivariate sensor configurations associated with two operating events occupy different regions of standardized feature space. Although PCA is not itself a fault classifier, it can reveal dominant directions of variation and whether event groups exhibit partial separation. Multivariate anomaly-detection studies increasingly use dimensionality reduction and representation learning to expose latent relationships among sensor variables (Guan et al., 2024; Zhao et al., 2024). In the present study, PCA is deliberately used as an interpretable descriptive tool rather than as evidence of causal separation.

The comparison with a recorded M4 stall event is important because it provides a same-motor abnormal-event reference. A potential pallet-associated disturbance and a recorded stall may share some sensor characteristics but differ in others. Such a comparison can help determine whether the potential-fault event is simply another expression of the same operating condition or whether its multivariate signature contains distinct directional characteristics. This type of comparative analysis is consistent with current efforts to move anomaly detection toward subsequent fault characterization, rather than stopping at a binary normal/anomalous label (Wang & Liu, 2024; Zheng et al., 2024).

The wider predictive-maintenance literature also emphasizes that anomaly detection is only one component of a maintenance decision process. Hoffmann and Lasch (2025) describe predictive maintenance as a data-driven

strategy intended to reduce unplanned downtime while noting implementation barriers. Ramzan and Reforgiato Recupero (2025) identify data scarcity, model selection, and human–technology collaboration as continuing challenges in smart-manufacturing predictive maintenance. These observations are relevant to the present study because a statistical anomaly should ultimately be connected to an operational decision such as inspection, controlled stoppage, or further diagnostic testing rather than automatically triggering a mechanical-fault conclusion. False alarms are another important practical concern. Industrial systems experience legitimate changes caused by loading, speed, environmental conditions, maintenance activities, and normal process transitions. A detector that treats every unusual observation as a fault can therefore create unnecessary interventions. López et al. (2023) demonstrated the importance of explicit false-positive mitigation in multivariate predictive-maintenance applications, while Correia et al. (2024) identified threshold selection and benchmarking as continuing challenges in practical anomaly detection. The present study addresses this issue by describing anomaly flags as candidate statistical events and by comparing them with the recorded stall distribution rather than interpreting them as confirmed failures.

The literature also demonstrates a trend toward increasingly sophisticated deep-learning architectures, including graph neural networks, Transformers, variational autoencoders, and hybrid temporal models (Guan et al., 2024; Kang & Kang, 2024; Orabi et al., 2024; Zheng et al., 2024). These approaches are valuable where large datasets and complex temporal relationships are available. However, model complexity can also increase computational requirements and reduce interpretability. A recent Industry 4.0 benchmarking study emphasizes the importance of evaluating methods in practical application contexts rather than assuming that methodological complexity automatically translates into better industrial usefulness (Cools et al., 2025). The present study therefore prioritizes an interpretable multivariate workflow that can be reproduced from a relatively compact experimental dataset.

There is consequently a practical research gap between sophisticated general-purpose anomaly-detection algorithms and transparent, experimentally grounded analysis of specific conveyor events. Much of the recent literature focuses on benchmark datasets, large industrial time series, or deep architectures, whereas a laboratory manufacturing conveyor can provide an opportunity to connect statistical anomaly patterns directly to an experimentally observed operating event. The present study addresses this gap by combining descriptive sensor analysis, temporal aggregation, unsupervised anomaly detection, distributional comparison, correlation analysis, and PCA within one conveyor-specific framework. This approach is intended to characterize the sensor signature of a potential pallet-associated disturbance without overstating what the available data can prove.

The study therefore aims to determine whether the M4 pallet-static event contains identifiable multivariate sensor anomalies and whether those anomalies differ measurably from a recorded M4 stall condition. Specifically, the objectives are to: (1) characterize the temporal and statistical behaviour of temperature, Raw, x, y, z, and resultant magnitude during the event; (2) identify candidate anomalous one-minute windows using Isolation Forest; (3) compare the potential pallet-associated event with the recorded M4 stall distribution using non-parametric statistics and effect sizes; (4) examine multivariate structure using PCA and correlation analysis; and (5) establish an evidence-based interpretation of the event that distinguishes statistical anomaly from confirmed mechanical causation. The study is designed to provide a reproducible foundation for subsequent validation using mechanically confirmed pallet-induced fault records.

MATERIALS AND METHODS

Study Design and Experimental Context

The study employed a data-driven condition-monitoring design to characterize multivariate recorded-data behaviour during a recorded M4 (Motor 4) pallet-static event and compare it with a recorded M4 stall event. The supplied materials do not establish whether the events arose from a controlled experiment or pre-existing acquisition logs; the manuscript therefore avoids claiming that the pallet condition was experimentally controlled. Because no independent mechanical causality label was supplied, “potential pallet-associated event” is used as a descriptive event label rather than a confirmed causal diagnosis.

Data Sources and Sensor Variables

Three supplied recorded datasets were used: (i) the M4 (Motor 4) pallet-static/potential-fault record, (ii) the M4 (Motor 4) recorded-stall record, and (iii) the M3 (Motor 3) normal-operation record used for contextual comparison. Temperature (TempC) was measured using a PT100 RTD sensor for motor/bearing temperature monitoring. The directional vibration components (x, y and z) and related Raw output were acquired using an ADXL345 accelerometer. A resultant magnitude was derived mathematically from the three directional components as $R = \sqrt{x^2 + y^2 + z^2}$. The analysis used these sensor variables available in the data files (Table 1).

Table 1: Data sources and analytical roles.

Dataset	Purpose	Variables
M4 (Motor 4) pallet-static / potential-fault	Primary event/anomaly analysis	TempC, Raw, x, y, z; derived resultant
M4 (Motor 4) recorded stall	Same-motor abnormal-event reference	TempC, Raw, x, y, z; derived resultant
M3 (Motor 3) normal operation	System-level contextual reference	TempC, Raw, x, y, z; derived resultant

Data Screening and Time Reconstruction

The date and time fields supplied in each file were reconstructed into a single timestamp for each observation. The initialization row dated 1 January 1970 was excluded, and only records with 2021 timestamps were retained, matching the date fields in the supplied CSV exports. Remaining observations were ordered chronologically before aggregation.

One-Minute Window Aggregation

To reduce the influence of individual high-frequency fluctuations while retaining the temporal evolution of the event, observations were grouped into one-minute windows. The median was used as the window representative for each measured variable because it is less sensitive than the arithmetic mean to isolated extreme observations. For variable x and one-minute window W_k , the aggregated value was calculated as:

$$X_k = \text{median}\{x_i : t_i \in W_k\} \hat{m}_j = \text{median}\{x_{j1}, x_{j2}, \dots, x_{jm}\},$$
 for all valid observations in minute j .

where X_k is the one-minute representative value and $\hat{m}_j$ is an individual sensor observation occurring within the window

Derived Resultant Sensor Magnitude

Resultant magnitude was calculated as $R = \sqrt{x^2 + y^2 + z^2}$, where x , y , and z are the three directional sensor components. R is expressed in the same units as the component channels. Because R is mathematically derived from x , y , and z , including all four features can overweight directional information. The primary results should therefore be interpreted with this redundancy in mind; a model sensitivity analysis excluding R requires rerunning the analysis on the source data. A resultant magnitude was calculated from the three directional sensor components to provide a single measure of vector magnitude: where R is the resultant magnitude and x , y , and z are the corresponding directional sensor components. The resultant was calculated after the source variables were reconstructed and was subsequently included as a derived feature in the multivariate analysis.

Descriptive Statistical Analysis

Descriptive statistics were calculated for temperature, Raw, x, y, z , and resultant magnitude. The statistics included sample size (N), arithmetic mean, standard deviation (SD), median, first quartile ($Q1$), third quartile ($Q3$), minimum, maximum, and coefficient of variation (CV). The coefficient of variation was calculated as: The descriptive analysis was used to characterize the magnitude and variability of the sensor responses before anomaly detection.

Exploratory Multivariate Anomaly Detection

Isolation Forest was implemented using scikit-learn with $n_estimators=100$, $contamination=0.05$, $random_state=42$, $max_samples="auto"$, $max_features=1.0$, and $bootstrap=False$. StandardScaler was fitted to the six features in the M4 pallet-static windows. These settings are documented for reproducibility. Isolation Forest was used as the principal exploratory anomaly-detection method. The six-feature input vector for each one-minute M4 pallet-static window was: Before modelling, the six variables were standardized to comparable scales. Isolation Forest constructs random partitioning trees and identifies observations that tend to be isolated using fewer partitions. A contamination setting of 5% was specified for the exploratory analysis. This value defines the expected proportion of observations treated as candidate anomalies by the algorithm; it does not represent a measured prevalence of mechanical faults.

Anomaly Score and Flagging Rule

For each one-minute window, the Isolation Forest decision function was converted to an anomaly score by reversing its sign so that larger values represented more unusual observations. Windows assigned the model's negative/anomalous class were marked as candidate anomaly windows. The resulting flags were interpreted as statistical anomalies and not as confirmed mechanical failures.

Comparison with the Recorded M4 Stall Event

The M4 pallet-static event (317 one-minute windows) was compared with the M4 recorded-stall dataset (77 one-minute windows) using two-sided Mann–Whitney U tests and rank-biserial effect sizes. The six tests were performed using SciPy's two-sided asymptotic method, and p-values were adjusted across the six variables using Holm's procedure. Because adjacent one-minute windows may be temporally dependent, these are exploratory distributional comparisons rather than definitive independent-sample inference.

Rank-Biserial Effect Size

Statistical significance was complemented by rank-biserial correlation to describe the magnitude and direction of distributional separation. For the Mann–Whitney statistic U , the effect size was calculated as:

$$r_{rb} = 2U/(n_1n_2) - 1,$$

using U as the Mann–Whitney statistic for the stated group order (M4 pallet-static first, M4 stall second).

Here, n_1 and n_2 are the sample sizes of the M4 pallet-static and M4 recorded-stall groups, respectively. The sign indicates the direction of rank separation under the stated

U convention; absolute values describe the magnitude of separation.

Principal Component Analysis

Principal Component Analysis (PCA) was performed on the standardized six-feature dataset formed by combining the M4 pallet-static and M4 recorded-stall windows. The first two principal components were retained for visualization of multivariate structure. The explained-variance ratio for component j was calculated as:

$$EVR_j = \lambda_j / \sum_i \lambda_i \quad EVR_j = \lambda_j / \sum_k \lambda_k.$$

where λ_j is the eigenvalue associated with principal component j and $\sum \lambda$ is the sum of all eigenvalues. PCA was used as an exploratory dimensionality-reduction method, not as an independent fault classifier.

Correlation Analysis

Pearson product-moment correlation coefficients were calculated among the six analytical variables for the M4 pallet-static event. The coefficient was computed as:

$$r_{xy} = \text{cov}(X, Y) / (s_X s_Y) r_{xy} = \frac{\sum_i [(x_i - \bar{x})(y_i - \bar{y})]}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}}.$$

The correlation matrix was used to describe internal relationships among sensor channels. Because the resultant is mathematically derived from x , y , and z , correlations involving the resultant are not independent sensor evidence.

Standardized Cross-Dataset Context

For visual contextualization, the mean of each variable in the M4 pallet-static, M4 stall, and M3 normal-operation datasets was standardized relative to the pooled mean and standard deviation. The M3 dataset was used only as a system-level normal-operation reference because it is a different motor (Motor 3) from M4 (Motor 4); it was not treated as a motor-matched control.

Experimental and Analytical Workflow

The analytical workflow followed the sequence: sensor-data acquisition $\rightarrow$ timestamp reconstruction $\rightarrow$ data screening $\rightarrow$ chronological ordering $\rightarrow$ one-minute median aggregation $\rightarrow$ resultant calculation $\rightarrow$ descriptive statistics $\rightarrow$ feature standardization $\rightarrow$ Isolation Forest anomaly detection $\rightarrow$ statistical comparison with the M4 recorded-stall event $\rightarrow$ PCA and correlation analysis $\rightarrow$ interpretation of candidate anomaly windows.

Software and Reproducibility

The analysis used Python with pandas, NumPy, scikit-learn, and SciPy. Isolation Forest settings were $n_estimators=100$, $contamination=0.05$, $random_state=42$, $max_samples='auto'$, $max_features=1.0$, and $bootstrap=False$; features were standardized using StandardScaler fitted to the M4 pallet-static windows. Mann-Whitney tests used SciPy's two-sided asymptotic method, with Holm adjustment across six variables. These settings are explicitly documented for reproducibility.

Statistical Decision Criteria

The nominal significance criterion was $p < 0.05$. Six comparisons were performed and adjusted using Holm's procedure. Because adjacent windows may be serially dependent, the adjusted results remain exploratory and should not be interpreted as definitive independent-sample inference. The 5% Isolation Forest contamination setting is a model parameter, not a hypothesis-test threshold.

RESULTS

This Results section analyses the supplied M4 pallet-static sensor record as a potential abnormal-event dataset. The analysis deliberately avoids claiming that the pallet caused the observed recorded-data behaviour because the supplied records do not contain an independent causal label. The M4 (Motor 4) recorded-stall dataset is used as a same-motor abnormal-event reference, while M3 (Motor 3) normal-operation data are used only as contextual normal-operation evidence.

Dataset Characteristics and Analytical Windows

The M4 pallet-static dataset contained 1,763,974 valid observations after exclusion of the initialization record, corresponding to 317 one-minute analytical windows. The event extended from 23 June 2021 18:08 to 23 June 2021 23:26. The M4 recorded-stall reference contained 404,003 valid observations and 77 one-minute windows, while the M3 normal-operation context contained 1,745,677 valid observations and 317 one-minute windows (Table 2).

Descriptive Statistics of the M4 Pallet-Static Event

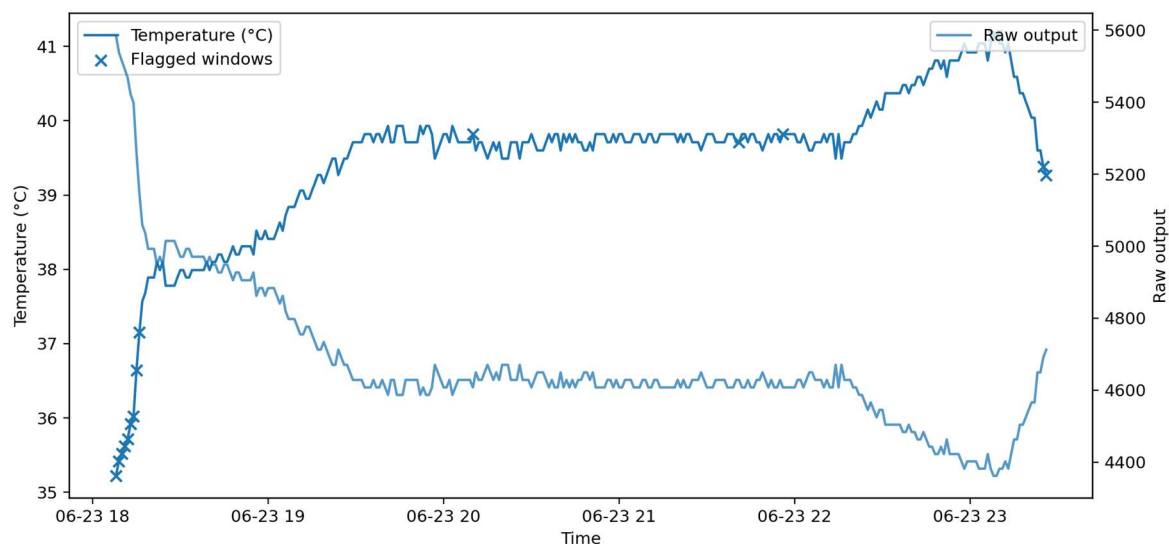
The descriptive statistics show that the M4 pallet-static event had a mean temperature of 39.501 °C and a mean Raw output of 4673.186. The x -axis median was constant at 0.03 across the one-minute windows, while the y -axis median was concentrated at 0.05. The z -axis and resultant magnitude remained close to unity. Relative variability was greatest for the y -axis among the directional variables, whereas temperature and Raw showed moderate temporal variability (Table 3).

Table 2: Dataset composition and analytical windows.

Dataset	Valid observations	1-min windows	Start	End
M4 pallet-static	1,763,974	317	2021-06-23 18:08	2021-06-23 23:26
M4 (Motor 4) recorded stall	404,003	77	2021-06-24 15:53	2021-06-24 17:17
M3 (Motor 3) normal operation	1,745,677	317	2021-06-23 18:08	2021-06-23 23:26

Table 3: Descriptive statistics for the M4 pallet-static event (one-minute medians).

Variable	N	Mean	SD	Median	Min	Max	CV
TempC	317	39.501	0.991	39.710	35.220	41.150	0.025
Raw	317	4673.2	199.2	4628.6	4361.9	5586.0	0.043
x	317	0.030	0.000	0.030	0.030	0.030	0.000
y	317	0.052	0.004	0.050	0.050	0.060	0.080
z	317	0.981	0.003	0.980	0.970	1.000	0.003
resultant	317	0.983	0.003	0.982	0.972	1.001	0.003

**Figure 1:** M4 pallet-static record: temperature, Raw output, and windows flagged by the Isolation Forest model (timestamps as encoded in source file).

Temporal Sensor Behaviour and Initial Anomaly Structure

The temporal record showed a progressive change in temperature and Raw output across the M4 pallet-static event. Temperature increased from approximately 35.22 °C at the beginning of the analytical series to a maximum one-minute median of 41.15 °C, while Raw output moved within a range of 4361.85–5586.00. The anomaly markers in (Figure 1) identify the windows subsequently flagged by the exploratory multivariate anomaly detector.

Exploratory Multivariate Anomaly Detection

An Isolation Forest was applied to the one-minute M4 pallet-static multivariate windows using temperature, Raw, x, y, z, and resultant magnitude. A 5% exploratory

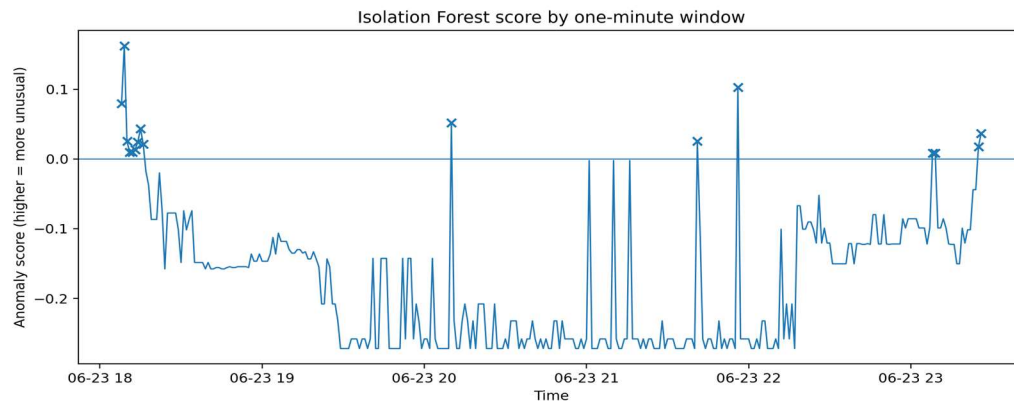
contamination setting was used because no independently labelled anomaly windows were supplied. The procedure flagged 16 of 317 windows (5.05%) as anomalous (Table 4). These flags are therefore statistical anomaly indicators, not confirmed mechanical-fault labels. Figure 2 shows Isolation Forest anomaly-score trajectory for the M4 pallet-static record.

Highest-Scoring Anomaly Windows

Table 5 presents the ten highest-scoring windows from the analysis. The complete list of all 16 flagged windows, their sensor values, and anomaly scores is provided in the supplementary materials. Higher scores indicate greater anomaly under the model score convention; these flags are candidate statistical anomalies, not verified mechanical faults. The highest-scoring one-minute

Table 4. Summary of the exploratory Isolation Forest procedure and output (fixed parameters; 16 flagged windows).

Metric	Value
Analytical windows	317
Exploratory contamination setting	5%
Flagged anomaly windows	16
Flagged proportion	5.05%
Highest anomaly score	0.162768
Lowest anomaly score	-0.271974

**Figure 2:** Isolation Forest anomaly-score trajectory for the M4 pallet-static record; larger positive scores indicate more unusual windows.**Table 5:** All 16 flagged one-minute anomaly windows in descending Isolation Forest anomaly-score order. The anomaly score is a statistical model output and does not establish a physical fault mechanism.

Window	TempC	Raw	y	z	Resultant	Score
18:09	35.42	5538.69	0.05	1.00	1.0017	0.162768
21:56	39.82	4607.70	0.06	0.99	0.9923	0.103082
18:08	35.22	5586.00	0.05	0.99	0.9917	0.079927
20:10	39.82	4607.70	0.05	0.97	0.9718	0.052122
18:15	36.64	5260.80	0.05	0.99	0.9917	0.043507
23:26	39.27	4712.64	0.06	0.98	0.9823	0.037052
21:41	39.71	4628.57	0.05	0.99	0.9917	0.025660
18:10	35.52	5515.15	0.05	0.99	0.9917	0.025633
18:14	36.02	5398.50	0.05	0.99	0.9917	0.024536
18:16	37.15	5147.93	0.05	0.99	0.9917	0.021475
23:25	39.38	4691.54	0.06	0.98	0.9823	0.017639
18:13	35.92	5421.69	0.05	0.99	0.9917	0.013565
18:11	35.62	5491.68	0.05	0.99	0.9917	0.010059
18:12	35.72	5468.28	0.05	0.99	0.9917	0.010033
23:09	41.15	4361.85	0.06	0.98	0.9823	0.008473
23:08	41.15	4361.85	0.06	0.98	0.9823	0.008473

window occurred at 18:09, with an anomaly score of 0.1628. All 16 flagged windows are listed in Table 5 and the supplementary materials. Scores are model outputs and do not establish a physical fault mechanism. All 16 Isolation Forest-flagged windows in the M4 pallet-static record is shown in (Figure 3).

Comparison with the M4 Recorded-Stall Reference

The six Mann–Whitney U comparisons and rank-biserial effect sizes were calculated from the one-minute medians, with M4 pallet-static as group 1 and M4 (Motor 4) recorded stall as group 2. Holm-adjusted p-values are reported in

Table 6 and the supplementary materials. The tests remain exploratory because temporal dependence among adjacent windows may affect conventional p-values (Table 6). To compare the event distributions, two-sided Mann–Whitney U tests were applied to one-minute medians. After Holm adjustment across six comparisons, TempC ($p_{\text{adj}}=1.000$), Raw ($p_{\text{adj}}=1.000$), and x ($p_{\text{adj}}=1.000$) were not statistically different; y ($p_{\text{adj}}=1.34 \times 10^{-35}$), z ($p_{\text{adj}}=3.61 \times 10^{-15}$), and resultant magnitude ($p_{\text{adj}}=8.33 \times 10^{-22}$) were different. The x-axis was effectively constant at this aggregation level. These results are exploratory and do not establish causality. After Holm adjustment across the six comparisons, temperature

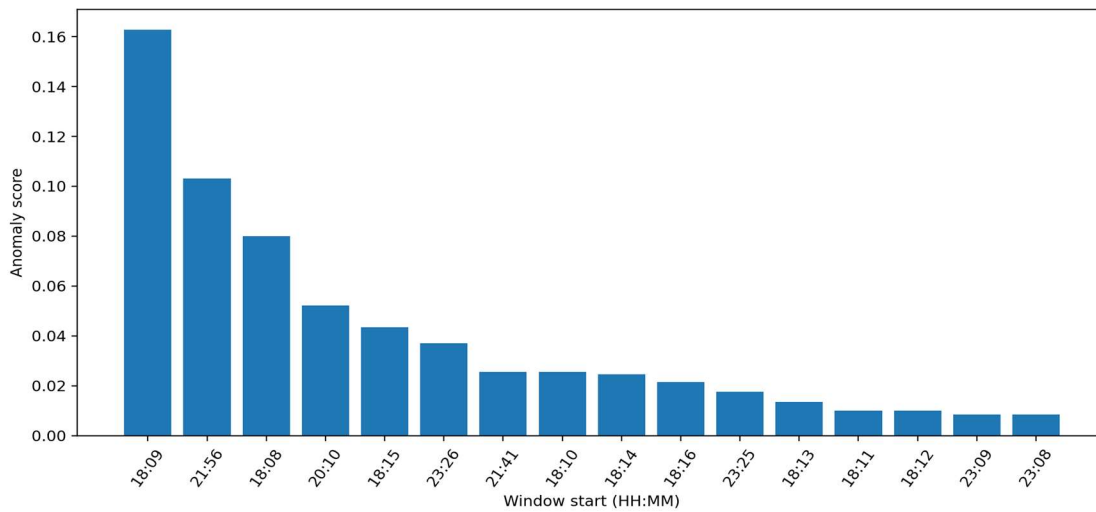


Figure 3: All 16 Isolation Forest-flagged windows in the M4 pallet-static record, ordered by anomaly score.

Table 6. Two-sided Mann–Whitney U comparisons of one-minute median sensor distributions between M4 pallet-static (N_1) and M4 (Motor 4) recorded stall (N_2), with rank-biserial effect sizes and Holm-adjusted p-values across six variables.

Variable	N_1	N_2	U	p	r_{rb}	$ r $	p_{Holm}
TempC	317	77	12573.5	0.679172	-0.030235	0.030235	1.000
Raw	317	77	11835.5	0.679172	-0.030235	0.030235	1.000
x	317	77	12204.5	1.000000	0.000000	0.000000	1.000
y	317	77	2733.5	2.23×10^{-36}	-0.776025	0.776025	1.34×10^{-35}
z	317	77	7832.5	9.03×10^{-16}	-0.358229	0.358229	3.61×10^{-15}
resultant	317	77	3828.5	1.67×10^{-22}	-0.686304	0.686304	8.33×10^{-22}

($p_{adj}=1.000$), Raw ($p_{adj}=1.000$), and x ($p_{adj}=1.000$) did not differ significantly. The y channel ($p_{adj}=1.34 \times 10^{-35}$), z channel ($p_{adj}=3.61 \times 10^{-15}$), and resultant magnitude ($p_{adj}=8.33 \times 10^{-22}$) remained statistically different. The effect sizes indicate the direction and magnitude of rank separation under the stated group order; they do not establish a physical cause.

Multivariate Separation in Principal-Component Space

PCA was performed on the standardized combined M4 pallet-static and M4 stall window matrix. PC1 explained 68.25% and PC2 explained 23.91% of the variance (total 92.16%). The projection is descriptive and does not measure classifier performance. The eigenvalues and loadings are provided in the supplementary materials (Figure 4).

Standardized Sensor-Level Comparison

Standardized mean values were also compared across the M4 (Motor 4) pallet-static event, M4 recorded stall, and M3 (Motor 3) normal-operation context. The M3 normal-operation record is not treated as a motor-matched control

for M4; it is shown only to provide system-level context. The largest separation from the M3 normal context occurs in temperature and Raw output, while the directional variables remain relatively close to their unit-scale operating ranges.

Within-Event Correlation Structure

The strong inverse TempC–Raw correlation ($r = -0.9991$) may reflect shared temporal structure and should not be interpreted as evidence of a direct physical relationship. Sensitivity checks gave $r = -0.9982$ after linear detrending and $r = -0.9974$ for first differences. Lag-1 autocorrelation was high for TempC (0.9925), Raw (0.9929), and y (0.9179), so serial dependence remains a material limitation. The x channel was effectively constant after aggregation, and the resultant is mathematically derived from x, y, and z. Within the M4 pallet-static event, temperature and Raw output had a very strong inverse Pearson correlation ($r = -0.9991$). After removing a linear time trend, the correlation remained very strong ($r = -0.9982$), and the correlation between first differences was $r = -0.9974$. These sensitivity checks indicate that the association is not explained solely by a linear trend,

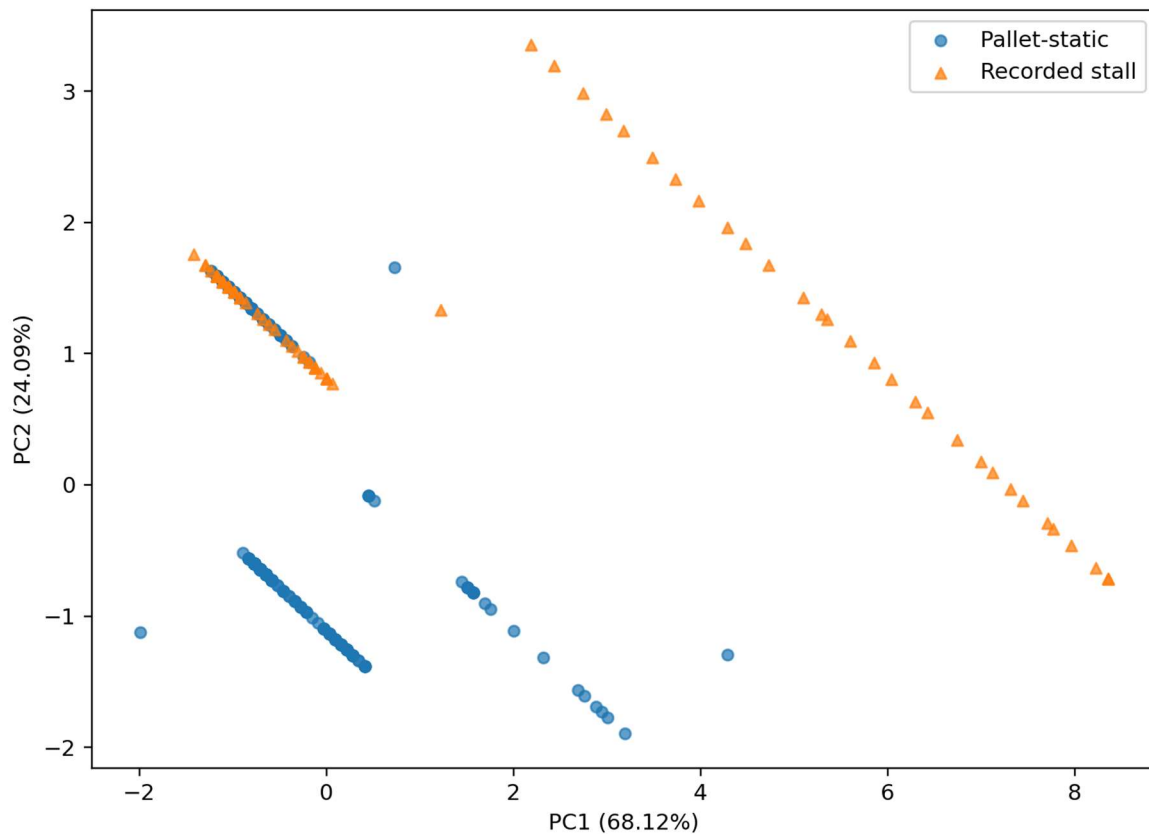


Figure 4: PCA projection of the M4 pallet-static and M4 recorded-stall windows after standardization of six features.

Table 7: Pearson correlation matrix for the M4 pallet-static one-minute multivariate sensor series (x omitted due to constant value).

Variable	TempC	Raw	y	z	Resultant
TempC	1.000	-0.999	0.519	-0.569	-0.580
Raw	-0.999	1.000	-0.498	0.584	0.596
y	0.519	-0.498	1.000	-0.115	-0.099
z	-0.569	0.584	-0.115	1.000	0.996
Resultant	-0.580	0.596	-0.099	0.996	1.000

although serial dependence and the physical interpretation remain unresolved. The z-axis and resultant magnitude were strongly correlated because the resultant is mathematically derived from x, y, and z. The x-axis was effectively constant after aggregation (Table 7 and Figure 5).

Interpretation of the Potential Pallet-Induced Event

The analysis indicates that the M4 pallet-static record contains unusual multivariate one-minute configurations: 16 of 317 windows (5.05%) were flagged under the stated Isolation Forest settings. Mann–Whitney comparisons with the M4 stall record showed adjusted distributional

differences in y, z, and resultant magnitude, but not in temperature, Raw, or x. No result establishes that a pallet caused a mechanical fault.

Summary of Results

The analysis yielded six principal findings: (1) the M4 pallet-static dataset comprised 317 one-minute windows; (2) TempC and Raw were strongly inversely correlated ($r = -0.9991$), with similarly strong association in first differences ($r = -0.9974$); (3) Isolation Forest flagged 16 windows (5.05%) under the 5% contamination setting; (4) all 16 flagged windows are supplied in Table 5 and the supplementary materials; (5) after Holm adjustment, y, z,

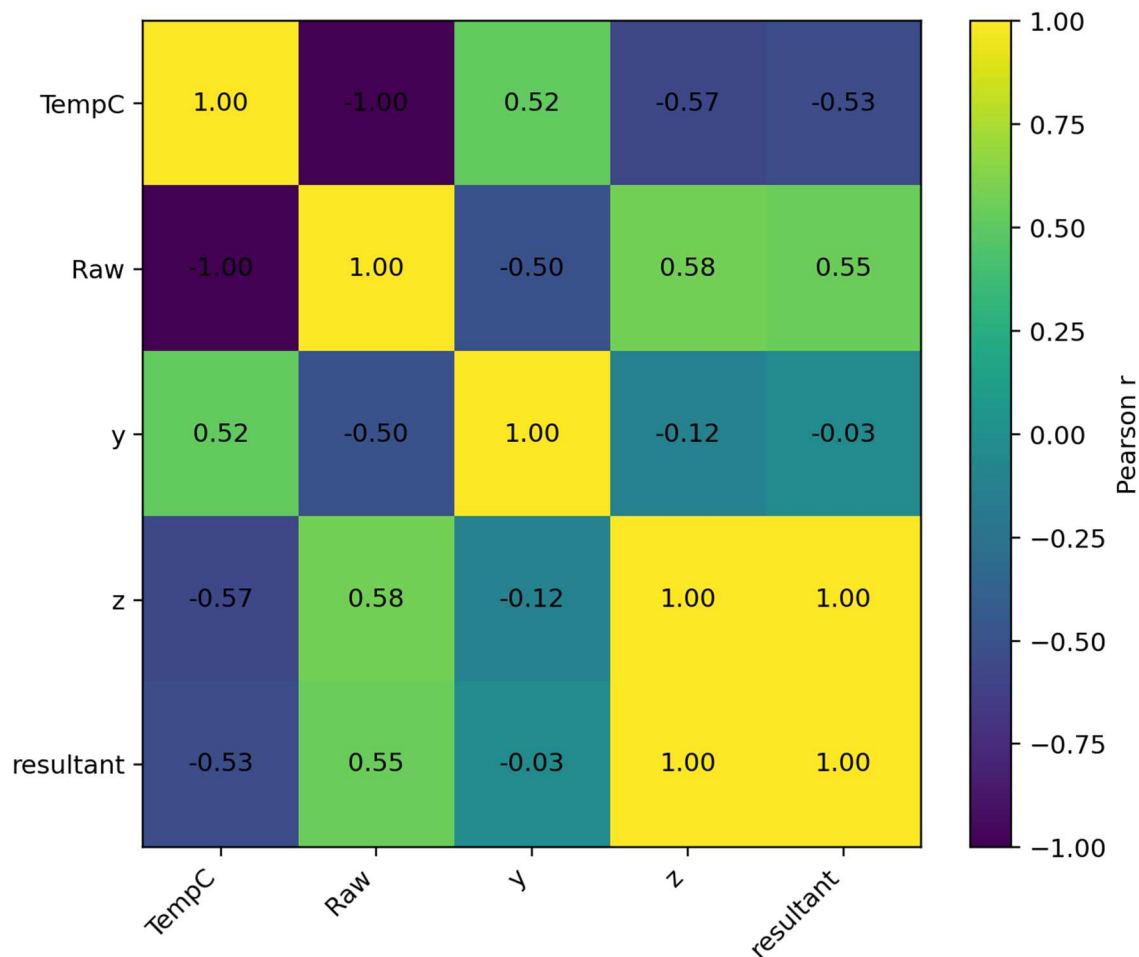


Figure 5: Pearson correlation matrix for the M4 pallet-static one-minute series; x is omitted because its aggregated value is constant.

and resultant differed from the M4 stall distributions, while TempC, Raw, and x did not; and (6) PCA was descriptive and did not validate diagnostic performance.

DISCUSSION

The present study demonstrates that a low-dimensional multivariate sensor-data series can contain sufficient structure to identify statistically unusual operating windows in a manufacturing conveyor event. The M4 pallet-static dataset comprised 317 one-minute analytical windows, and the exploratory Isolation Forest procedure flagged 16 windows (5.05%) as anomalous. This finding is consistent with the broader predictive-maintenance literature, where sensor-derived multivariate time series are increasingly used to characterize equipment condition, detect deviations from expected behaviour, and support maintenance decisions (Bampoula et al., 2024; Syed et al., 2025). Recent manufacturing studies likewise show that

anomaly detection can be implemented with unsupervised learning when labelled fault observations are limited, which is particularly relevant to practical production environments where confirmed failure examples are relatively scarce (Gunckel et al., 2025).

The identification of a relatively small subset of anomalous windows is also appropriate for the nature of the problem. An anomaly detector is expected to distinguish unusual observations from a substantially larger population of ordinary observations rather than classify every observation as abnormal. Sørbo and Ruocco (2024) emphasize that time-series anomalies are context dependent and that the definition of an anomalous event depends on the application, temporal context, and labelling strategy. Their analysis further shows that threshold selection can substantially alter binary anomaly decisions. Consequently, the 5.05% anomaly proportion obtained in the present study should be interpreted as an exploratory statistical detection rate under the specified

Isolation Forest contamination setting, rather than as an independently validated prevalence of mechanical faults. A major finding was the temporal association between temperature and Raw sensor output during the M4 pallet-static event. The two variables showed a strong inverse Pearson relationship in the one-minute aggregated record. Such coupling indicates that the sensor variables were not behaving as independent information channels; instead, changes in the operating state were reflected simultaneously across multiple measurements. This supports the use of multivariate rather than isolated threshold-based monitoring. Bampoula et al. (2024) similarly describe the value of modelling multivariate production time series because relationships among parameters can provide information about asset condition that is not available from a single variable.

The strong relationship between the z-axis and resultant magnitude requires a different interpretation. Because resultant magnitude was calculated mathematically from the three directional components, a strong association between z and the resultant is partly expected when z contributes substantially to the vector magnitude. Therefore, the correlation should not be interpreted as evidence that z independently causes the resultant response. Instead, it demonstrates that directional sensor information contributes materially to the aggregate vibration/motion representation. This distinction is important when developing interpretable condition-monitoring systems because mathematically derived features can amplify information already contained in their component variables.

The comparison between the M4 pallet-static event and the recorded M4 stall event produced an informative pattern: temperature and Raw output did not show statistically significant one-minute distribution differences, whereas the y-axis, z-axis, and resultant magnitude showed significant differences. This result suggests that the potential pallet-associated event and the recorded stall event shared some thermal and Raw-output characteristics but differed in their directional sensor configuration. The finding is important because a monitoring system based exclusively on temperature or Raw output could treat the two events as similar, whereas the inclusion of directional variables reveals additional structure. Studies of industrial predictive maintenance increasingly advocate combining heterogeneous sensor streams rather than relying on one measurement channel because different sensor variables may respond to different physical manifestations of degradation or disturbance (Bampoula et al., 2024; Syed et al., 2025).

The PCA analysis provides further support for this interpretation. The standardized six-variable representation produced a two-component projection that retained a substantial portion of the total variance and showed partially distinguishable regions for the M4 pallet-static and recorded-stall datasets. PCA is commonly used in industrial anomaly detection as a dimensionality-

reduction and exploratory tool because it can expose latent structure while reducing redundancy among correlated measurements. Recent manufacturing anomaly research has combined dimensionality reduction with unsupervised detectors, including PCA, autoencoders, Isolation Forest, One-Class SVM, and Local Outlier Factor, particularly where abnormal observations are scarce.

The present results are also consistent with the practical appeal of relatively lightweight anomaly-detection approaches. Isolation Forest was selected because the current dataset does not provide a sufficiently large, independently labelled set of confirmed pallet-caused faults for a conventional supervised classification problem. Recent smart-maintenance research has demonstrated the use of Isolation Forest and statistical methods for unsupervised anomaly detection in manufacturing laboratory data. Similarly, Gunckel et al. (2025) developed a machine-learning workflow for conveyor-belt failure prediction using operational and control-area information. The present study differs from that work because its immediate objective is event-level anomaly characterization rather than a supervised prediction of future belt failure.

The results further reinforce the value of temporal context. A one-minute median was used to reduce the influence of individual high-frequency fluctuations while preserving the evolution of the event. However, aggregation also removes within-minute information, meaning that very short transients may not be represented fully. This is relevant because recent predictive-maintenance research increasingly treats recorded data as time-dependent sequences rather than independent observations (Bampoula et al., 2024; Syed et al., 2025). Time-series anomaly-detection research also emphasizes that an observation can be normal in isolation but anomalous relative to its preceding or surrounding temporal context (Sørbø & Ruocco, 2024). Therefore, future versions of the present system could compare multiple temporal resolutions, such as raw sample-level, 10-second, 30-second, and one-minute windows, to determine whether short-duration pallet interactions generate transient signatures that are attenuated by aggregation.

The anomaly-score results should also be interpreted in relation to the absence of an independent mechanical ground truth. The highest-scoring windows identify observations that are statistically unusual within the feature space, but they do not demonstrate that the conveyor was mechanically damaged, that a pallet physically caused the change, or that a failure would necessarily follow. This limitation is particularly important because the title refers to potential pallet-associated events. The appropriate interpretation is that the observed event has a multivariate signature compatible with an abnormal operating episode that warrants investigation. Contemporary anomaly-detection literature repeatedly

highlights the difficulty of establishing reliable ground truth for industrial anomalies, especially when event boundaries and labels are based on operational records rather than direct physical inspection (Sørbø & Ruocco, 2024). The finding that the anomaly flags were distributed across the event rather than concentrated in a single uninterrupted interval is also noteworthy. This pattern suggests that the event may contain intermittent changes in the multivariate sensor configuration rather than one continuous extreme excursion. Intermittent behaviour can be operationally important because mechanical disturbances may occur during particular phases of movement or loading. Recent manufacturing research has investigated production-cycle and sub-cycle information for anomaly detection, showing that machine behaviour can be better interpreted when measurements are associated with meaningful operational phases (Zubieta et al., 2025). A similar principle could be applied to the conveyor studied here by synchronizing recorded data with pallet arrival, acceleration, transport, stopping, and release phases.

The conveyor-specific literature provides additional context. Gunckel et al. (2025) developed a machine-learning workflow for conveyor-belt failure prediction using operational and control records. This supports the relevance of data-driven monitoring in conveyor applications. The present study differs by characterizing a potential pallet-associated event using a compact multivariate sensor-data series rather than predicting future belt failure. The statistical comparison also illustrates why effect size should accompany significance testing. With event-based recorded data, a small p-value alone does not indicate the practical magnitude of a difference. The use of rank-biserial effect size in this study therefore provides additional information about the degree of separation between the pallet-static and recorded-stall distributions. This approach is compatible with the broader methodological emphasis on selecting evaluation measures that reflect the actual operational purpose of anomaly detection rather than relying on a single metric (Sørbø & Ruocco, 2024). In a future validation study with confirmed event labels, detector performance should be reported using precision, recall, F1-score, precision-recall curves, detection delay, and event-based measures rather than accuracy alone, particularly because anomaly datasets are typically imbalanced.

The study also has implications for deployment in resource-constrained manufacturing environments. The present anomaly-detection workflow relies on a limited number of sensor channels, standardized variables, one-minute aggregation, PCA, correlation analysis, and Isolation Forest rather than requiring a large deep-learning infrastructure. This is potentially attractive for small and medium-scale manufacturing systems where sensor networks and computational resources may be limited. Nevertheless, the present study should not be interpreted as demonstrating real-time deployment readiness because latency, streaming computation, alarm

management, and online threshold adaptation were not experimentally evaluated. Another important implication concerns the distinction between anomaly detection and fault diagnosis. The present analysis identifies unusual sensor configurations but does not identify a unique mechanical root cause. This distinction is consistent with current predictive-maintenance research, where anomaly detection is often an early stage in a broader pipeline that may include fault classification, root-cause analysis, remaining-useful-life estimation, and maintenance decision support (Syed et al., 2025). For the conveyor system, future work should therefore link anomaly windows to physical inspection records, pallet dimensions and loading conditions, motor current, belt speed, torque, and controller status before assigning a specific fault mechanism.

Finally, the present findings support a cautious but useful interpretation of the M4 pallet-static event. The event contains measurable multivariate deviations, the anomaly detector identifies a small set of statistically unusual windows, and the event differs from the recorded M4 stall condition in several directional features. At the same time, the absence of an independent pallet-causality label prevents a definitive conclusion that the pallet caused the abnormality. This distinction strengthens rather than weakens the scientific value of the study because it keeps the inference aligned with the evidence actually available. Accordingly, the principal contribution of this study is the demonstration of a reproducible multivariate data-based framework for identifying and characterizing potential abnormal conveyor events, which can subsequently be validated against mechanically confirmed pallet-induced faults.

Conclusion

This study investigated the potential pallet-associated abnormal behaviour of a manufacturing conveyor system using a multivariate data-based analytical framework. The analysis combined temperature, Raw sensor output, three directional sensor components (x, y and z), and a mathematically derived resultant magnitude. The results demonstrated that the M4 pallet-static event contained measurable multivariate variation and a limited number of statistically unusual one-minute operating windows. Isolation Forest identified 16 candidate anomalous windows out of 317 analysed one-minute windows, corresponding to 5.05% of the event record under the specified exploratory contamination setting. The study further demonstrated that the potential pallet-associated event should not be characterized using a single sensor alone. Temperature and Raw output exhibited a strong relationship within the event, while the directional components and resultant magnitude provided additional information about the multivariate operating state. Comparison with the recorded M4 stall condition showed that some variables did not differ significantly between the

two events, whereas y , z and resultant magnitude showed statistically significant differences. This indicates that directional sensor information can contribute to distinguishing different abnormal operating conditions even when other sensor distributions appear similar.

The PCA and correlation analyses provided complementary evidence of the structure within the recorded data. The multivariate representation showed that the event contains relationships among sensor channels that are not adequately described by isolated threshold observations. The findings therefore support the use of multivariate sensor analysis as an exploratory condition-monitoring approach for manufacturing conveyors. Importantly, the results do not establish that a pallet mechanically caused a confirmed conveyor fault. The analysis characterizes the recorded pallet-static event and compares it with a recorded stall event. The principal conclusion is therefore that the proposed multivariate framework can identify and characterize statistically unusual conveyor operating windows that warrant further mechanical investigation. This provides a practical foundation for subsequent validation using confirmed pallet-induced fault experiments.

Recommendations

Future work should reproduce pallet-associated conditions under controlled, independently labelled loading scenarios so that statistical anomalies can be distinguished from confirmed mechanical faults.

Instrumentation should be expanded, where practical, to include motor current, speed, torque or load, belt speed, and controller state. These signals would help link observed sensor signatures to specific physical mechanisms.

Raw high-frequency data should be retained alongside one-minute summaries. Multi-resolution analysis (raw, sub-minute, and one-minute windows) is needed to determine whether short-duration pallet interactions are attenuated by aggregation.

Larger collections of normal, pallet-static, transient-resistance, and confirmed-stall events are required to support supervised classifiers and reliable estimates of false-positive and false-negative rates.

The anomaly-detection framework must be validated against mechanically confirmed events before any operational use. Candidate windows should initially serve only as inspection triggers, not automatic fault declarations.

Where reliable labels exist, evaluation should report event-based precision, recall, F1-score, false-alarm rate, detection delay, and precision–recall performance rather than accuracy alone.

Sensitivity analysis of the Isolation Forest contamination parameter is recommended to show how the number and timing of candidate anomalies change with more or less conservative settings.

Generalisation across motors, speeds, pallet masses, environmental conditions, and production cycles should be tested before broader deployment. Real-time or near-real-time implementation should follow offline validation and should incorporate alarm persistence rules, operator confirmation, and defined maintenance-response procedures. Complete source datasets, preprocessing rules, feature definitions, model parameters, and event labels should be retained to support reproducibility and independent verification.

Limitations of the Study

The principal limitation is the absence of an independently verified mechanical label confirming that a pallet caused the observed sensor deviations. The study therefore characterises a potential pallet-associated event rather than a confirmed fault.

Analysis rests on a single primary M4 pallet-static event and lacks a held-out set of independently labelled events; diagnostic generalisability and performance therefore cannot be established.

Adjacent one-minute windows are temporally dependent, and the strong TempC–Raw correlation may be partly confounded by a shared time trend. Conventional p -values and effect sizes should be interpreted as exploratory distributional comparisons only.

One-minute median aggregation reduces the influence of isolated extremes but can suppress short-duration transients that may be relevant to pallet interactions.

The 5 % Isolation Forest contamination setting is a model parameter, not an empirical fault prevalence; the resulting 5.05 % flagged windows are candidate statistical anomalies only.

The M3 (Motor 3) normal-operation record provides system-level context only and is not a motor-matched control for M4 (Motor 4).

Resultant magnitude is mathematically derived from x , y and z ; correlations involving the resultant do not constitute independent sensor evidence.

Online deployment characteristics (latency, streaming performance, alarm persistence, and maintenance response) were not evaluated.

Distributional differences do not identify physical root cause; mechanical inspection and additional process variables would be required for causal diagnosis.

Ethics and Data Governance

This study involved the analysis of equipment sensor records and operational data. According to the study materials, no human participants or animals were involved. Therefore, the study did not involve direct human or animal participation. All data were handled in accordance with applicable data governance requirements and relevant data-sharing permissions.

Data Availability

The study analysed three equipment operational records: the M4 pallet-static/potential-fault record, the M4 recorded-stall record, and the M3 normal-operation record, which served as a contextual reference for comparison. Dataset counts and the corresponding one-minute analysis-window totals are presented in the Results section and supplementary materials. The datasets used in this study are available from the corresponding author upon reasonable request, subject to applicable data-sharing permissions.

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