Transaction on Machine Design

DLINE JOURNALS

ISSN: 2438-442X
TMD 2026: 14 (2)
https://doi.org/10.6025/tmd/2026/14/2/85-97

A Dynamic Causal-Network Framework for Predictive Maintenance and Degradation Analysis in Manufacturing Systems

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ABSTRACT

Traditional predictive maintenance often lacks interpretability and fails to uncover the underlying physical mechanisms of equipment degradation. To address this critical gap, this study proposes a dynamic causal network framework that transitions maintenance strategies from purely predictive to fully prescriptive. Utilizing a comprehensive industrial machine sensor dataset, the research employs a multi stage analytical methodology integrating correlation analysis, mutual information, Granger causality testing, and rolling window dynamic network analysis.

The empirical results reveal exceptionally strong linear and nonlinear dependencies among core operational variables, particularly temperature, vibration, and pressure. Furthermore, Granger causality analysis establishes directional information flows, successfully identifying vibration as a critical precursor to defect generation. Crucially, the rolling window analysis demonstrates that causal connectivity is non stationary and fluctuates significantly over time. Periods of elevated causal density correspond to degradation accumulation or abnormal system behaviors, while reduced connectivity indicates post maintenance recovery or stable operation.

These findings indicate that machine health is reflected not only in individual sensor magnitudes but also in the evolving structural interactions among variables. Consequently, dynamic causal connectivity serves as a novel, highly interpretable health indicator. By uncovering the directional propagation of degradation, the proposed framework provides actionable insights for root cause diagnosis and early fault detection, ultimately supporting more proactive, targeted, and efficient maintenance decision making in smart manufacturing environments.

Keywords: Predictive Maintenance, Causal Discovery, Granger Causality, Dynamic Causal Networks Machine Health Assessment, Smart Manufacturing, Fault Propagation, Root Cause Diagnosis

Received: 27 September 2025, Revised 11 February 2026, Accepted 1 March 2026

1. Introduction

Maintenance has evolved from a support function to a strategic component of industrial operations, directly influencing operational safety, asset longevity, productivity, and cost efficiency. Consequently, it is increasingly recognized as a cooperative partner and profit contributor within organizational planning processes [1, 2]. The growing complexity of modern industrial systems, together with increasing demands for reliability and operational continuity, has accelerated the adoption of advanced maintenance strategies that anticipate equipment degradation before failures occur.

Among the various maintenance paradigms proposed to address these challenges, predictive maintenance has emerged as one of the most promising approaches, leveraging operational data to anticipate equipment degradation and failure. Understanding the evolution of predictive maintenance and its associated analytical techniques, therefore, provides the foundation for examining recent developments in causal discovery and machine health assessment.

2. Related Studies

Among these strategies, Predictive Maintenance (PdM) has emerged as a key enabler of smart manufacturing and Industry 4.0. By leveraging sensor measurements, operational data, and machine learning techniques, PdM systems aim to forecast impending failures and assess equipment health. Although existing predictive maintenance approaches have demonstrated considerable success in predicting failures, they often offer limited insight into the underlying causes of degradation and failure propagation. This limitation becomes particularly pronounced in industrial environments characterized by dynamic operating conditions, evolving process interactions, and nonstationary sensor signals. Many existing approaches rely on static causal assumptions or segmented analyses that fail to capture continuously changing system dynamics [3].

While predictive maintenance systems can successfully forecast failures, their practical value is often constrained by limited interpretability. Industrial practitioners increasingly require explanations of why degradation occurs and how faults propagate through interconnected processes. This requirement has stimulated growing interest in causal modeling approaches capable of uncovering the underlying mechanisms that drive system behavior.

The construction, validation, and updating of causal models in industrial settings have traditionally relied on process experts possessing extensive domain knowledge and a deep understanding of physical process behavior [4]. However, rapid technological advancements have introduced increasingly complex industrial infrastructures composed of numerous interconnected components, sophisticated control systems, and highly interactive subsystems. Such systems exhibit nonlinear behavior, dynamic operating conditions, and evolving degradation mechanisms that challenge conventional expert driven modeling approaches [5]. As noted by Alizadeh, Koujok, Ragab, and Amazouz [6], reliance on human expertise alone is becoming insufficient for accurately characterizing the intricate relationships embedded within modern industrial processes. Consequently, developing accurate and continuously adaptive causal models has become a major challenge in predictive maintenance research.

Causality is a particularly valuable form of maintenance knowledge because it directly reflects the physical mechanisms by which degradation and failure propagate. Unlike correlation, causality describes directional relationships in which one state exerts a deterministic or probabilistic influence on another, and that influence persists under intervention or manipulation [7]. In industrial equipment monitoring, where sensor measurements are collected continuously over time, causality must be interpreted within a temporal framework. According to the principle of temporal precedence, a cause must occur before its effect [8]. This concept is especially relevant in industrial sensor systems, where equipment behavior is represented by multivariate time-series data characterized by complex temporal dependencies and mechanical interactions.

One of the most influential formulations of temporal causality was proposed by Granger [9] who defined causality in terms of predictability. A variable is said to Granger cause another variable if information contained in its past values significantly improves the prediction of the future values of the second variable beyond what can be achieved using only the latter's own historical observations. Building upon this principle, causal discovery seeks to identify, quantify, and characterize causal relationships directly from observational data [10, 11]. The objective is to determine the existence, strength, and direction of influence among variables without requiring complete prior knowledge of system structure.

In industrial maintenance applications, causal relationships are rarely known a priori. Traditionally, their identification has depended on engineering expertise, manual investigations, and post failure analyses. Such approaches are often time consuming, costly, and susceptible to incomplete or inaccurate interpretations. The increasing availability of continuous sensor streams has therefore motivated the development of automated, data driven causal discovery approaches that learn system interactions directly from operational data. By combining computational causal discovery algorithms with temporal dependency analysis, these approaches provide a pathway to prescriptive maintenance by revealing the mechanisms underlying equipment degradation rather than merely detecting its symptoms.

The advantages of causal discovery extend beyond fault detection. Data-driven causal models can identify root causes associated with specific component interactions, environmental influences, and operational stress conditions. Consequently, they provide engineers with mechanistic explanations of degradation processes and failure propagation pathways. Such insights enable targeted maintenance actions, more efficient resource allocation, and the prevention of cascading failures before they become operationally critical. As emphasized by Rotari and Kulahci [12] the transition from predictive maintenance toward prescriptive maintenance requires the discovery of causal relationships that support actionable operational interventions rather than reliance on statistical associations alone.

Causal discovery has received increasing attention across diverse domains, including healthcare [13] mineral economics [14], and transportation systems [15]. Its application within industrial maintenance remains relatively limited [16, 17]. In particular, research focusing on sensor data driven causal discovery methods for equipment maintenance is still in its early stages, and only a limited number of studies have investigated the extraction of causal structures from continuous industrial sensor streams [18, 19, 20].

The importance of causal discovery becomes particularly evident when considering quality-related degradation phenomena in manufacturing systems. Because operational faults often propagate through multiple interconnected process variables, understanding causal relationships provides a natural pathway for identifying the origins and progression of performance deterioration.

Simultaneously, manufacturing industries are facing increasing challenges associated with functional degradation and quality-related faults. Root-cause diagnosis has become a critical requirement for maintaining product quality and ensuring efficient production performance [21]. Recent research on manufacturing systems has expanded beyond the detection of discrete failures to encompass broader issues, including functional degradation, operational resilience, and performance deterioration in complex production environments [22, 23]. Unlike catastrophic failures, functional faults often manifest as subtle deviations from nominal operating behavior that gradually reduce system performance while remaining undetected by traditional monitoring systems.

To address these challenges, researchers have increasingly emphasized the integration of machine learning, real time monitoring, and advanced analytics for detecting latent performance degradation in intelligent manufacturing systems [24, 25]. Recent studies further advocate combining fault detection, prognostics, and predictive analytics to identify early indicators of degradation before catastrophic failures occur [26]. Similarly, adaptive diagnostic frameworks that integrate anomaly detection with fault tolerant control strategies have emerged as promising solutions for maintaining operational continuity under degraded conditions [27, 28]. Collectively, these developments indicate a paradigm shift toward holistic fault management strategies that treat functional degradation as a fundamental research problem requiring integrated sensing, modeling, diagnostic, and control methodologies [22, 29, 30].

Despite these advances, a significant research gap remains. Most existing predictive maintenance studies focus primarily on condition monitoring, fault classification, and failure prediction, while comparatively little attention has been paid to uncovering the causal structures that govern the progression of degradation and quality deterioration in manufacturing systems. Furthermore, the application of dynamic causal discovery techniques to industrial sensor data remains limited, particularly in continuously evolving manufacturing environments. Addressing this gap requires analytical frameworks that combine sensor-based monitoring with causal inference methods to identify not only when failures are likely to occur but also why they emerge and how they propagate through complex production systems.

To address these limitations and advance the transition from predictive to prescriptive maintenance, the present study develops a dynamic causal network framework to identify evolving dependencies among machine-health variables and production quality indicators. By integrating correlation analysis, information-theoretic dependency measures, Granger causality modeling, and time-varying causal network analysis, the proposed framework seeks to uncover the evolving interaction structures underlying machine degradation and production-quality performance. The resulting insights contribute toward the development of more interpretable, proactive, and prescriptive maintenance strategies for smart manufacturing environments.

3. Dataset Description

3.1 Dataset Overview

The empirical analyses were conducted using the *Machine Sensor Dataset* developed by Mustafa Harashi and made publicly available through Kaggle. The dataset was designed to simulate realistic industrial machine-monitoring environments and provides a comprehensive framework for predictive maintenance, anomaly detection, and smart manufacturing research. By integrating continuous sensor telemetry with maintenance and failure records, the dataset enables the investigation of machine degradation dynamics, operational performance, and maintenance effectiveness.

Data were collected from four industrial machines throughout 2024, with sensor measurements recorded at 5-minute intervals. The dataset comprises three interrelated files linked through a common machine identifier. The primary sensor dataset contains 421,632 observations of machine operating conditions, while complementary files document 28 failure events and 48 maintenance interventions. This integrated structure facilitates both condition monitoring analyses and event-driven prognostic investigations.

3.2 Data Structure and Characteristics

The sensor dataset contains multivariate time-series measurements describing machine operating behavior. Key variables include machine temperature, vibration intensity, hydraulic pressure, production count, defect count, and operational status indicators. These measurements provide a detailed representation of machine condition and production performance over time.

The failure log records critical information about machine breakdowns, including failure onset times, detection timestamps, severity classifications, failure types, and root cause information. The maintenance log captures preventive and corrective interventions, documenting technician information, components replaced, maintenance costs, and downtime.

The dataset exhibits several characteristics that make it suitable for predictive maintenance research. First, the high temporal resolution supports dynamic monitoring and time series modeling. Second, the integration of sensor streams with failure and maintenance records enables prognostic analyses linking operational behavior to future system states. Finally, the rarity of failure events relative to normal operating conditions reflects realistic industrial environments and creates opportunities for investigating imbalanced learning and early-warning systems.

3.3 Potential Applications and Limitations

The dataset supports a wide range of industrial analytics, including anomaly detection, failure prediction, reliability assessment, maintenance optimization, and remaining useful life estimation. Researchers can derive health indicators from sensor streams, construct predictive maintenance models, and investigate degradation pathways leading to failure.

Despite its strengths, several limitations should be acknowledged. The dataset is synthetic and represents only four machines, potentially limiting its generalizability to broader industrial populations. Failure events are relatively sparse, which may influence predictive modeling performance. Furthermore, external contextual variables such as operator behavior, environmental conditions, and supply chain factors are not included. Nevertheless, the dataset provides a valuable testbed for evaluating advanced prognostic and health-management methodologies.

Given these characteristics, the dataset provides an appropriate environment for constructing and evaluating a dynamic causal analysis framework. Consequently, a dedicated predictive-maintenance testbed was designed to integrate sensor telemetry, maintenance records, and causal discovery techniques within a unified analytical architecture.

3.4 Dynamic Causal Predictive Maintenance Testbed Architecture

The proposed study employs a data centric predictive maintenance testbed designed to investigate the evolving causal relationships among machine health variables and production-quality indicators. The architecture integrates continuous sensor monitoring, event based maintenance data, and dynamic causal analytics into a unified framework that supports machine health assessment and predictive maintenance decision making.

The testbed is built upon three interconnected data layers. The first layer consists of the machine telemetry acquisition system, which continuously collects operational measurements from four industrial machines at five-minute intervals throughout the observation period. This layer captures key machine-condition indicators, including temperature, vibration intensity, hydraulic pressure, production output, and defect generation metrics. These sensor streams provide a high resolution representation of machine behavior and operational performance.

The second layer comprises the maintenance and failure event management subsystem. Maintenance records include preventive and corrective interventions, replaced components, maintenance costs, and downtime information, while failure logs document fault occurrence times, severity levels, failure categories, and identified root causes. The integration of event information with sensor telemetry enables the temporal alignment of operational behavior with maintenance actions and failure outcomes.

The third layer consists of the analytical intelligence engine, which extracts operational dependencies and causal structures from the collected data. Initially, sensor streams undergo preprocessing procedures including timestamp synchronization, missing value handling, and feature standardization. The processed data are subsequently analyzed using multiple complementary techniques. Correlation analysis is employed to identify linear relationships among operational variables, while Spearman correlation and mutual information analysis capture monotonic and nonlinear dependencies. These analyses provide an initial representation of system connectivity and variable interdependence.

To uncover directional interactions, the architecture incorporates a Granger causality module that assesses whether historical observations of one variable improve predictions of future observations of another. Significant causal relationships are represented as directed edges within a causal network, thereby revealing information flow pathways among machine health indicators and production quality variables. The resulting network serves as a dynamic representation of process behavior and degradation propagation.

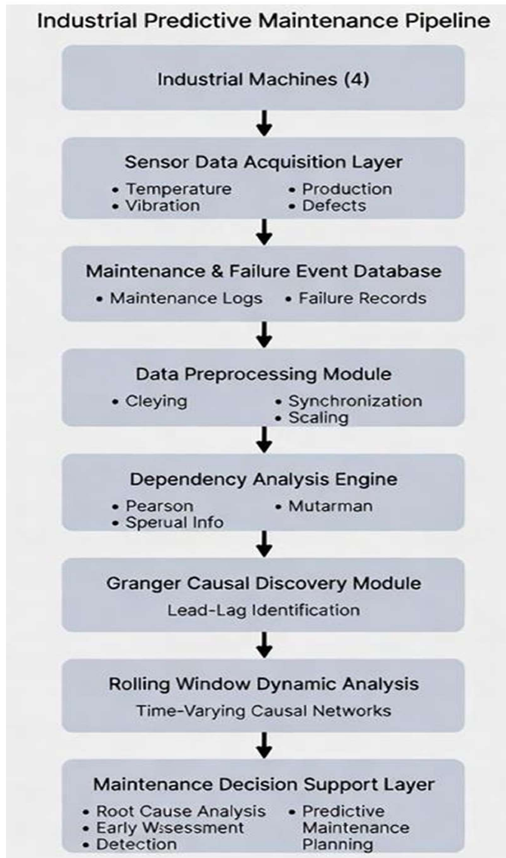

Figure 1. Dynamic Causal Predictive Maintenance Design

To account for nonstationary operating conditions, a rolling window causal discovery mechanism is integrated into the architecture. Instead of estimating a single static causal structure, causal relationships are recalculated over sequential temporal windows. This approach enables the detection of evolving interaction patterns, changes in network connectivity, and shifts in system behavior associated with degradation accumulation, maintenance interventions, or abnormal operating states. The dynamic causal network, therefore, functions as a machine health representation that captures both variable magnitudes and the changing structure of inter variable dependencies.

The final layer of the testbed is the decision support module. Outputs generated by the causal network engine, including connectivity measures, lead lag relationships, and temporal causal density indicators, are transformed into interpretable maintenance knowledge. These outputs support root-cause analysis, early-warning detection, degradation monitoring, and predictive maintenance planning. By combining operational sensor measurements with dynamic causal inference, the proposed architecture extends traditional condition-monitoring systems toward a more prescriptive maintenance paradigm that explains not only when failures may occur but also how degradation propagates throughout the manufacturing system.

Figure 1 illustrates the overall architecture of the proposed Dynamic Causal Predictive Maintenance Testbed, showing the flow from sensor acquisition and event logging through preprocessing, causal discovery, dynamic network analysis, and maintenance decision support.

The proposed architecture establishes the computational infrastructure through which machine-health information is acquired, processed, and transformed into causal knowledge. Building upon this framework, the following methodology describes the analytical procedures used to quantify dependencies, identify causal interactions, and evaluate their temporal evolution.

4. Methodology

To investigate the relationships between machine health dynamics and production quality, a multi stage analytical framework was developed. The framework combines correlation analysis, information theoretic dependency analysis, Granger causality modeling, and dynamic causal network assessment.

Initially, Pearson correlation coefficients were computed to evaluate linear dependencies among temperature, vibration, pressure, production output, and defect generation. Spearman rank correlations were subsequently employed to assess monotonic relationships and reduce sensitivity to non normal distributions. Mutual information analysis was then conducted to quantify nonlinear dependencies among variables.

To move beyond static association analysis, Granger-causality testing was performed to identify temporal predictive relationships among process variables. Significant causal interactions were represented through a lead lag network, enabling visualization of directional information flow within the manufacturing system.

Finally, a rolling-window Granger causality analysis was implemented to capture temporal evolution in system connectivity. This dynamic framework provides insight into how machine-health relationships change during different operational states and degradation phases.

Application of the proposed analytical framework produced a series of complementary insights into the structure, dynamics, and causal behavior of the manufacturing system. The results are presented sequentially, beginning with static dependency analysis and progressing toward dynamic causal network assessment.

Collectively, these analytical stages form a progressive dependency discovery hierarchy in which correlation analysis identifies associations, mutual information reveals nonlinear dependencies, Granger causality establishes directional influence, and rolling window analysis captures the temporal evolution of causal structures. This hierarchy enables increasingly deeper characterization of machine health dynamics.

5. Results and Discussion

5.1 Correlation Structure of the Manufacturing System

Table 1 presents the Pearson correlation matrix for the five principal operational variables.

Variable	**Temper - ature**	**Vibration**	**Pressure**	**Produ -ction**	**Defects**
Temperature	1.000	0.974	0.976	0.957	0.544
Vibration	0.974	1.000	0.928	0.900	0.589
Pressure	0.976	0.928	1.000	0.988	0.480
Production	0.957	0.900	0.988	1.000	0.466
Defects	0.544	0.589	0.480	0.466	1.000

Table 1. Pearson correlation matrix among operational variables

The correlation matrix reveals an exceptionally strong coupling among temperature, vibration, pressure, and production output. Correlation coefficients exceeding 0.90 indicate that these variables evolve in a highly synchronized manner during machine operation. The strongest relationship was observed between pressure and production output (r = 0.988), indicating that production throughput is closely associated with process pressure.

Defect generation exhibited only moderate correlations with operational variables. Although defect counts increased with rising vibration and temperature levels, the relationships were substantially weaker than those observed among operational variables. This finding suggests that product quality is influenced not only by machine condition but also by additional latent factors not directly captured by the available sensors.

Figure 2 illustrates the corresponding correlation network, where edge strengths represent the magnitude of pairwise dependencies. The network highlights temperature, vibration, and pressure as highly connected variables occupying central positions within the manufacturing process.

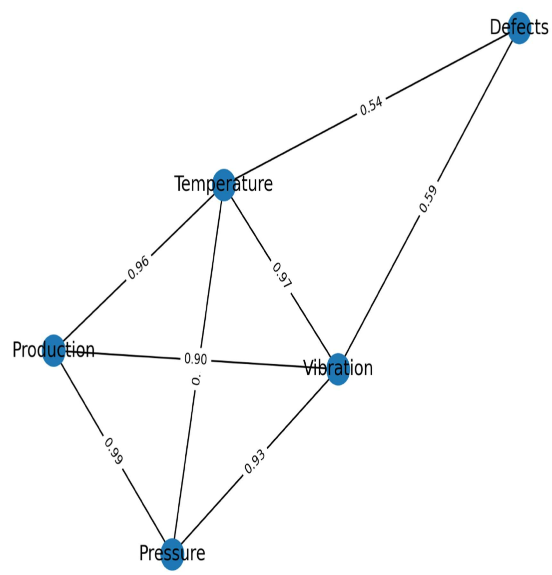

Figure 2. Correlation network among operational variables

Although Pearson correlations reveal strong linear relationships among operational variables, industrial processes frequently exhibit nonlinear and non-monotonic behavior. Additional dependency measures were therefore examined to determine whether the observed relationships persist beyond linear assumptions.

5.2 Monotonic and Nonlinear Dependencies

Spearman's rank correlation confirmed the robustness of the observed relationships. Strong positive monotonic associations were identified between temperature and vibration (ρ=0.849), pressure and production (ρ= 0.881), and temperature and production (ρ = 0.753). The persistence of these relationships under rank-based analysis indicates that the observed dependencies are not solely driven by linear effects.

To further investigate nonlinear interactions, mutual information analysis was performed. The highest information sharing relationships were observed between temperature and vibration (MI≈1.10), vibration and pressure (MI ≈1.04), and temperature and pressure (MI ≈ 0.98). These findings demonstrate substantial nonlinear dependencies among operational variables and suggest the existence of complex interaction mechanisms governing machine behavior.

Collectively, the correlation and mutual-information analyses indicate that the manufacturing process operates as a tightly integrated system in which changes in one operational variable propagate throughout the network.

5.3 Causal Relationships and Lead–Lag Dynamics

While correlation analysis identifies associations, it does not reveal directional relationships. Therefore, Granger causality testing was employed to determine whether changes in one variable systematically precede changes in another.

The causality matrix demonstrated numerous statistically significant predictive relationships among operational variables. Temperature was found to significantly precede changes in vibration and production, while pressure exhibited a strong predictive influence on production output. Similarly, vibration showed a predictive relationship with defect generation, indicating its potential as an early warning indicator of quality degradation.

The resulting lead lag network, shown in Figure 2, contains nineteen significant causal connections. This dense network structure demonstrates that machine variables interact dynamically rather than independently.

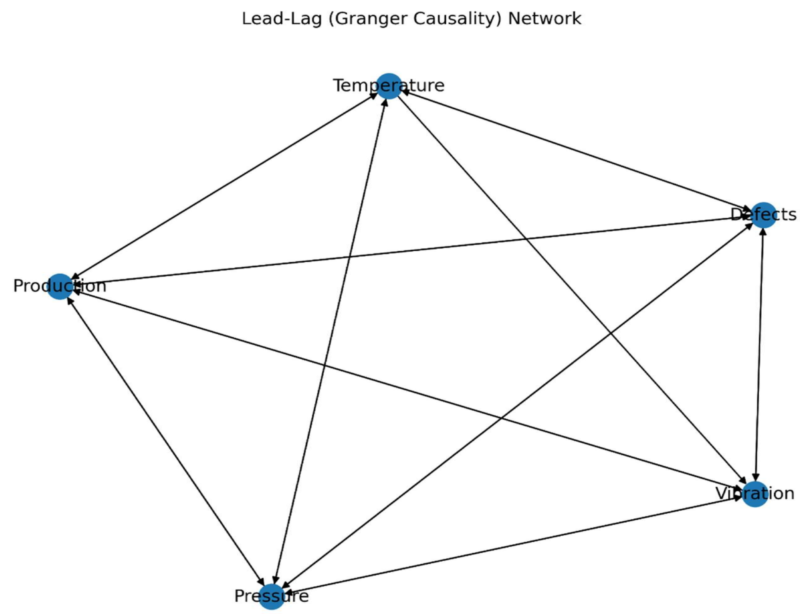

Figure 3. Lead–lag network derived from Granger-causality analysis

The presence of extensive directional connectivity suggests that operational changes propagate throughout the manufacturing process, reinforcing the need for integrated monitoring approaches rather than isolated sensor evaluation.

The lead lag network provides a static representation of directional interactions across the entire observation period. However, manufacturing systems operate under evolving conditions in which causal relationships may strengthen, weaken, or disappear over time. Consequently, a dynamic analysis was undertaken to examine the temporal evolution of causal connectivity.

5.4 Time-Varying Causal Dynamics

To investigate temporal changes in system behavior, rolling-window Granger-causality analysis was performed. Instead of estimating a single causality structure for the entire dataset, causal relationships were recalculated across sequential windows, enabling assessment of dynamic connectivity patterns.

Figure 3 presents the evolution of significant causal links over time. The number of significant relationships

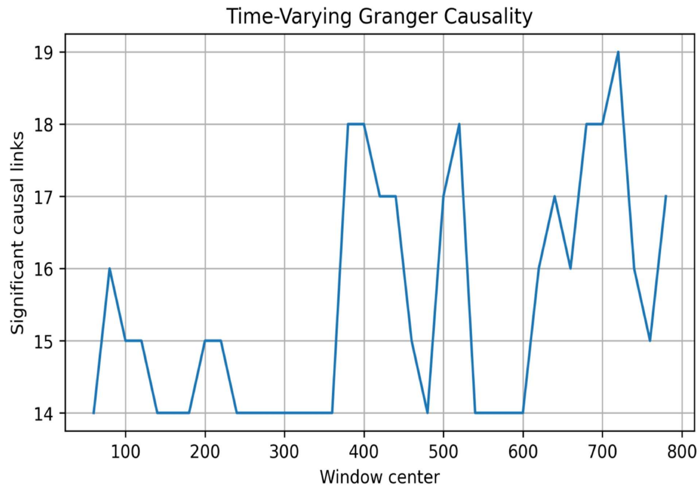

Figure 4. Rolling Granger-causality analysis showing temporal evolution of significant causal links

fluctuated between 14 and 19, indicating that system connectivity was not stationary. Several periods exhibited increased causal density, particularly around windows 380–420, 520–540, and 680–720, where the number of significant interactions approached the theoretical maximum.

These periods of elevated connectivity may correspond to intensified operational coupling, degradation accumulation, or the onset of abnormal machine behavior. Conversely, intervals characterized by lower connectivity may reflect recovery periods following maintenance interventions or stable operating conditions.

The observed temporal variations in causal connectivity have important practical implications for machine-health monitoring and maintenance decision-making. Translating these findings into actionable maintenance knowledge is therefore essential for assessing their operational significance.

5.5 Implications for Predictive Maintenance

The combined findings provide strong evidence that temperature, vibration, and pressure function as core indicators of machine condition. Their high levels of correlation, mutual information, and causal influence indicate that they collectively define the operational state of the manufacturing system.

Furthermore, the temporal evolution of causal connectivity suggests that degradation processes may manifest through increasing interdependence among operational variables before observable failures occur. This finding supports the development of dynamic health indices, hidden state models, and prognostic frameworks that exploit evolving network structures for early fault detection and remaining useful life estimation.

Overall, the results demonstrate that causal network analysis offers a powerful extension to traditional condition monitoring approaches by capturing both the magnitude and directionality of machine health interactions.

An important observation from the dynamic analysis is that degradation may manifest not only in abnormal sensor values but also in structural changes in the causal network itself. Increasing connectivity density suggests intensified coupling among operational variables, potentially indicating growing system stress. This observation supports the concept of network based health indicators that can complement conventional condition monitoring metrics.

6. Discussion and Conclusion

Taken together, the preceding results reveal a consistent progression from statistical association to dynamic causal interaction. The combination of dependency analysis, causal inference, and time-varying network assessment provides a comprehensive view of how machine health variables collectively shape manufacturing performance. Using a multi-stage analytical framework combining correlation analysis, mutual information, Granger causality, and rolling-window causal dynamics the research examined sensor telemetry, failure records, and maintenance logs from four industrial machines.

The results demonstrate that the manufacturing process operates as a tightly integrated system. Temperature, vibration, and pressure exhibit exceptionally strong linear and nonlinear dependencies, with pairwise correlations exceeding 0.90 in many cases. These variables occupy central positions in the process network, and their high mutual information values confirm substantial nonlinear information sharing. Critically, however, defect generation showed only moderate correlations with operational variables, suggesting that product quality is influenced by additional latent factors not fully captured by the available sensors.

The Granger-causality analysis extended these findings by revealing directional predictive relationships. Temperature preceded changes in vibration and production; pressure strongly predicted production output; and vibration emerged as a precursor to defect generation, indicating its potential utility as an early warning indicator of quality degradation. The resulting lead lag network contained nineteen significant causal connections, confirming that machine variables interact dynamically rather than independently.

Perhaps the most significant finding emerged from the rolling-window Granger causality analysis. System connectivity was not stationary; the number of significant causal links fluctuated between 14 and 19 over time. Periods of elevated causal density notably around windows 380–420, 520–540, and 680–720 may correspond to the accumulation of degradation or the onset of abnormal behaviour, while intervals of lower connectivity may reflect post maintenance recovery or stable operation. This temporal evolution suggests that machine health is reflected not only in sensor magnitudes but also in the changing *pattern of interactions* among operational variables.

In conclusion, the analytical framework developed in this study demonstrates that causal network analysis offers a powerful extension to conventional predictive maintenance approaches. By capturing both the strength and directionality of machinehealth interactions, dynamic causal connectivity can serve as a valuable health indicator. These findings support the development of prognostic frameworks that exploit evolving network structures for early fault detection, remaining useful life estimation, and more targeted maintenance decision-making. Future work should investigate the integration of exogenous factors (e.g., operator behaviour, environmental conditions) and validate these causal indicators against real world failure events.

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