From Sensor Data to Maintenance Actions: An Industrial PHM Application for Ultrasonic Welding Assembly Machines

Francesco Cancelliere[1], Morena Ferrario[2]

[1,2] *MECH-I-TRONIC, Milan, Lombardy, 20123, Italy*
francesco.cancelliere@mechitronic.com
morena.ferrario@mechitronic.com

Abstract

Ultrasonic welding machines are widely used in high-precision manufacturing processes, where progressive component degradation can lead to quality losses, increased reject rates, and unplanned downtime. Although modern machines generate large volumes of high-frequency process data, such as welding time, amplitude, and pressure, deploying effective predictive maintenance solutions remains challenging due to strong process variability, the lack of explicit failure labels, and the absence of historical run-to-failure datasets. This paper presents an industrial Prognostics and Health Management (PHM) framework developed for a multi-station ultrasonic welding machine used in pharmaceutical assembly, with the objective of enabling early detection of performance degradation and supporting predictive maintenance decisions. The proposed approach focuses on the construction of an interpretable, data-driven health indicator at component level, derived from sensor data and explicitly designed to be understandable by machine experts. Domain knowledge provided by the machine manufacturer is integrated to interpret the health indicator evolution and to translate detected degradation patterns into concrete maintenance recommendations. A healthy reference behavior is established using data from machines operating under stable conditions, enabling relative deviation analysis and trend-based monitoring across heterogeneous stations. The framework was deployed in an industrial pilot and demonstrated the ability to identify abnormal behaviors associated with component wear and process sensitivity, including cases where conventional maintenance actions showed limited effectiveness. The results indicate that the proposed indicators can reveal degradation patterns earlier than traditional reject-rate monitoring, thereby supporting maintenance prioritization at component level. This work illustrates how interpretable, data-driven PHM methodologies, co-designed with machine experts, can be successfully integrated into real manufacturing environments, bridging the gap between raw process data and actionable maintenance insights.

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1. Introduction

The increasing digitalization of manufacturing systems has opened new opportunities for improving equipment reliability and production efficiency through data-driven maintenance strategies. In the context of Industry 4.0, modern industrial machines generate large volumes of high-frequency operational data through embedded sensors and control systems. These data streams enable the development of advanced Prognostics and Health Management (PHM) approaches aimed at detecting performance degradation, anticipating failures, and optimizing maintenance planning. By leveraging process data and machine connectivity, predictive maintenance has the potential to reduce unplanned downtime, minimize scrap rates, and extend component lifetime (Zio, 2022).

Despite these opportunities, the deployment of predictive maintenance in real industrial environments remains challenging. Many production systems operate under highly variable conditions, with limited availability of labeled failure data and scarce run-to-failure histories (Calabrese, Regattieri, Botti, & Galizia, 2019; Fernandes, Corchado, & Marreiros, 2022). This is particularly true for complex manufacturing equipment used in high-precision industries such as pharmaceutical or medical device assembly, where machines are typically maintained preventively to avoid quality risks. As a result, purely data-driven approaches that rely on large failure datasets are often difficult to apply in practice, as highlighted in recent reviews, where the lack of real industrial datasets and the strong dependence of machine learning models on large amounts of labeled data are identified as key limitations (Polverino et al., 2023).

Among manufacturing systems, automated assembly machines represent a particularly challenging domain for PHM applications. These machines typically involve multiple interacting stations performing tightly coupled operations, where performance degradation may arise from a combination of mechanical wear, tooling degradation, alignment issues, or process variability. Several studies have investigated condition monitoring and predictive maintenance for manufacturing equipment using machine learning or statistical methods, often focusing on machining processes, rotating machinery, or bearing diagnostics (Li & Gryllias, 2024). However, comparatively fewer works address PHM in assembly systems, where degradation patterns are often subtle, process-dependent, and difficult to isolate at component level.

Ultrasonic welding is a key process widely used in high-precision assembly industries, including pharmaceutical packaging, medical devices, and electronics manufacturing. The process relies on high-frequency mechanical vibrations to generate localized heating and material bonding, requiring precise control of parameters such as welding time, amplitude, pressure, and energy. Progressive degradation of machine components (such as welding tools, mechanical guides, or actuators) can alter the dynamic behavior of the process, potentially leading to increased reject rates or unstable weld quality (Tian et al., 2023). While ultrasonic welding machines generate a large amount of process data through their control systems, leveraging these data for predictive maintenance remains largely unexplored in industrial practice.

A further challenge in deploying PHM solutions for such machines lies in bridging the gap between data-driven analytics and domain expertise (Lukens & Markham, 2018). Machine manufacturers and maintenance experts possess valuable knowledge regarding machine physics, component interactions, and typical degradation mechanisms. Integrating this expert knowledge with data-driven indicators is therefore essential to ensure that detected anomalies can be interpreted and translated into actionable maintenance decisions. Interpretable indicators and transparent monitoring approaches are particularly important in industrial contexts where lack of transparency can limit adoption and trust in condition-monitoring system (Kim, Lee, Kim, Yoon, & Youn, 2025).

This paper presents an industrial PHM framework developed for a multi-station ultrasonic welding machine used in pharmaceutical assembly. The primary objective of this work is to demonstrate a practical industrial PHM application developed under real production constraints and operational requirements, rather than to introduce a novel theoretical PHM architecture. The proposed approach focuses on the construction of interpretable health indicators derived from process sensor data already available in the machine control system, without requiring the installation of additional sensors.

This choice was motivated by the need to ensure compatibility with real industrial deployment constraints, including machine accessibility, production continuity, and implementation costs. The framework emphasizes component-level monitoring, enabling the identification of localized degradation patterns across stations. A healthy reference behavior is established using data collected from the machine operating under stable conditions, allowing relative deviation analysis and trend monitoring over time. In practice, this reference is designed to be dynamic, supporting continuous refinement as new data becomes available and machine conditions evolve, though such adaptation is not explored in this paper.

A key aspect of the proposed methodology is the integration of domain knowledge provided by machine experts to interpret health indicator evolution and relate observed deviations to potential physical causes.

In industrial environments, purely data-driven approaches may face practical limitations in terms of interpretability and acceptance by maintenance teams. For this reason, the interaction between monitoring indicators and expert interpretation was considered a central aspect of the proposed industrial workflow. This collaboration enables the translation of data-driven signals into practical maintenance insights and supports decision-making for component replacement or process adjustment.

The main contributions of this work are therefore threefold:

- The development of an interpretable, data-driven PHM framework tailored for multi-station ultrasonic welding machines operating under real industrial constraints.
- The definition of component-level health indicators derived from existing process data without requiring additional instrumentation or machine modifications.
- The demonstration of how expert knowledge can be integrated with data analytics to translate degradation signals into actionable maintenance recommendations in a real industrial environment.

The proposed framework was deployed in an industrial pilot and evaluated using operational data from production machines. The results show that the proposed indicators can reveal degradation patterns earlier than traditional reject-rate monitoring, supporting proactive maintenance planning and improved process understanding.

2. SYSTEM AND DATA DESCRIPTION

Among the various stations of the assembly machine, the ultrasonic welding station represents one of the most critical operations in terms of added value and process sensitivity. In addition, this station provides the largest amount of process data through embedded sensors and control variables. For these reasons, this work focuses specifically on monitoring the welding stations in order to detect early signs of degradation affecting the welding process.

Ultrasonic welding machines are widely used in high-precision manufacturing processes to join thermoplastic components without the use of adhesives or additional materials. The process relies on high-frequency mechanical vibrations, typically in the range of tens of kilohertz, which are transmitted through a welding tool (sonotrode) to the parts to be joined. These vibrations generate localized frictional heating at the interface of the plastic components, allowing the material to soften and form a solid bond once the vibration stops and pressure is maintained (Silva, da Silva, Morelli, López, & Santos, 2025).

In the industrial application considered in this work, ultrasonic welding is used to join two plastic components as part of a pharmaceutical assembly process. The welding operation must ensure consistent mechanical strength and tightness while maintaining very strict quality standards. Any deviation in the welding conditions can lead to defective joints and consequently to rejected products. For this reason, maintaining stable machine behavior is essential to guarantee both production efficiency and product quality (Faes et al., 2025).

A typical ultrasonic welding station is composed of several interacting mechanical elements. The sonotrode transfers the ultrasonic vibrations generated by the welding system to the plastic part, while the lower tooling supports and positions the component during the welding cycle. In the machine considered in this study, the lower tooling includes a component referred to as the *Body Lower*, which contains a vertically moving piston responsible for bringing the part into contact with the sonotrode during the welding operation. Proper alignment, motion precision, and mechanical stability of these components are critical to ensure repeatable welding conditions.

The machine under study is a continuous-motion ultrasonic welding system composed of sixteen welding pins operating in parallel. Unlike indexed machines, where the system stops at each station to perform the operation, this machine operates in continuous motion. Parts move continuously along the machine while the welding operation is performed dynamically (Neyret Group, 2023). This architecture allows the machine to reach very high production rates, up to 400 pieces per minute. However, the continuous motion configuration also introduces additional challenges. The high production speed leaves limited tolerance for process disturbances, and even small mechanical deviations or component wear can quickly propagate into quality losses or increased reject rates. As a consequence, early detection of abnormal behavior is essential to prevent production disruptions and to support timely maintenance interventions. The welding operation is performed through sixteen identical pins distributed around the machine 1. Each pin includes the mechanical elements required to position and press the part against the sonotrode during the welding cycle. The Body Lower component contains a piston that moves vertically to bring the part into contact with the welding tool and to apply the required pressure during the process. Over time, mechanical wear, alignment issues, or friction variations in these components may alter the dynamics of the welding operation, potentially affecting the stability of the process.

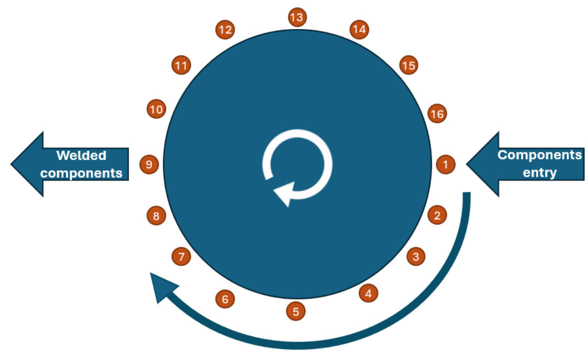

Figure 1. Schematic representation of the continuous-motion ultrasonic welding machine with the sixteen welding pins.

The machine control system provides access to several process variables measured during each welding cycle. These signals include parameters related to the welding process such as welding time, amplitude, energy, and force-related variables. All data are available through the machine programmable logic controller (PLC) and can be accessed externally via an OPC UA communication interface. This enables the acquisition of high-frequency production data without interfering with the machine operation.

In this work, the monitoring approach relies exclusively on the data already available within the machine control system, without introducing additional sensors. This choice is motivated by two main reasons. First, modifying industrial machines by adding instrumentation may require mechanical changes, validation procedures, and potential certification updates, which are often impractical in regulated production environments. Second, minimizing additional hardware requirements improves the scalability and economic viability of the proposed solution. Leveraging existing process data therefore represents an attractive approach for deploying predictive maintenance solutions in real industrial settings.

Since each welding cycle generates process data for each individual pin, the monitoring approach focuses on analysing the behavior at pin level. This allows the identification of localized degradation patterns that may not be visible when considering the overall machine behavior.

Among the variables available from the machine control system, several process parameters are recorded for each welding operation. The main variables considered are summarized in Table 1. These variables provide information about the duration, energy input, vibration characteristics, and mechanical

Table 1. Main process variables available from the welding station.

Variable	Unit	Description
WeldTime	ms	Duration of ultrasonic vibration during the welding cycle
Energy	J	Total ultrasonic energy delivered during welding
Amplitude	μm	Relative vibration amplitude of the sonotrode
Collapse	mm	Measured displacement during the welding process
Weld Pressure	bar	Pressure applied during the welding phase

response of the welding process, and are therefore relevant indicators of the stability of the welding operation.

These signals are recorded for every welding cycle and for each individual pin, enabling the collection of large volumes of production data during normal machine operation. The availability of these variables provides an opportunity to monitor the welding process using existing machine data and to detect deviations that may indicate mechanical degradation or process instability.

3. PROPOSED PHM FRAMEWORK

Deploying predictive maintenance solutions in industrial environments often presents several practical challenges. In the case considered in this study, no historical dataset of failures or run-to-failure sequences is available. In addition, no explicit labels describing past failures or degradation states exist in the production data. These limitations make the application of supervised learning approaches impractical, as the training of such models typically requires large amounts of labeled examples of normal and faulty behavior (Lei et al., 2020).

Another difficulty arises from the nature of the welding process itself. Variability is inherent to the manufacturing process due to factors such as material tolerances, part positioning, and operational conditions (Brito et al., 2023). As a consequence, distinguishing between normal process variability and early signs of mechanical degradation is not straightforward. This context motivates the development of monitoring approaches capable of detecting subtle deviations in process behavior without relying on labeled failure data (Oviedo et al., 2025).

For these reasons, the framework proposed in this work follows an unsupervised monitoring strategy. The key idea is to define a reference representation of healthy machine behavior and to continuously monitor deviations from this baseline. The underlying hypothesis is that progressive degradation of machine components will eventually affect the statistical properties of the available process signals, such as their variability, distribution shape, or temporal evolution. By identifying deviations from the reference behavior, it becomes possible to detect early signs of abnormal process dynamics.

An important aspect of the proposed approach is the integration of expert knowledge into the monitoring process. While data-driven indicators can reveal deviations from normal behavior, interpreting the physical meaning of these deviations often requires domain expertise. In this work, the analysis of the monitoring results is therefore complemented by the interpretation provided by machine experts and the equipment manufacturer. This collaboration enables the identification of the most likely causes behind detected anomalies, such as degradation of the sonotrode, variations in piston motion, or other mechanical issues affecting the welding station.

Over time, the analysis of detected anomalies and their associated root causes can contribute to the construction of a knowledge base describing typical degradation patterns of the machine. As new anomaly patterns are observed and validated, this knowledge can be progressively structured and reused. This process opens the possibility of gradually moving toward a semi-supervised monitoring approach, where previously observed degradation dynamics can be recognized more rapidly and associated with probable fault causes.

The ultimate objective of the framework is therefore not only to detect abnormal machine behavior, but also to support maintenance decision-making. When an anomaly is detected, the system aims to provide maintenance teams with alerts associated with a probable cause of the fault, allowing faster troubleshooting and targeted interventions. This can help prevent unexpected failures, reduce production losses, and limit the increase of reject rates that may occur when degradation remains undetected.

The overall monitoring framework, shown in Fig. 2, follows a structured sequence of steps. First, process data are continuously collected from the machine control system. These data are then analyzed and compared with the reference healthy behavior using several health indicators that capture different aspects of the signal dynamics, such as variability, distribution shape, and temporal trends. When significant deviations from the reference behavior are detected, an alarm is generated. The detected anomaly is then reviewed together with machine experts in order to identify the most probable cause and determine whether a maintenance action is required. Finally, the information is communicated to the maintenance team, allowing them to monitor the situation closely or intervene before the degradation leads to machine failure or excessive reject rates.

4. USE CASE

To demonstrate the validity of the proposed approach, we present a case study involving the detection of an abnormal pattern in one of the machine pins. Fig. 3 compares the av-

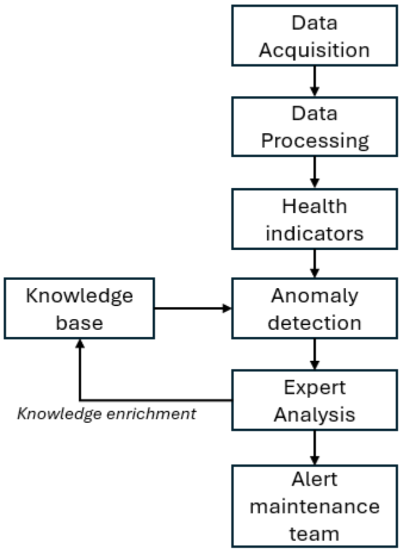

Figure 2. Overview of the proposed PHM framework combining data-driven monitoring and expert interpretation.

erage welding time of a well-functioning pin with that of Pin 12, where an anomalous behavior is observed. For confidentiality reasons, the y-axis values of welding time in this paper are displayed after a linear transformation. This operation preserves all temporal patterns and does not affect the proposed monitoring indicators.

As mentioned, during the industrial pilot, multiple monitoring indicators were investigated and monitored in parallel, including indicators related to process variability and distribution shape. However, in this paper we focus specifically on a Fast Fourier Transform (FFT) Peak Ratio indicator, as it provided, within the short duration of the pilot project, the most complete and representative validation of the proposed PHM framework. In particular, this use case demonstrates the full monitoring loop: the health indicator enabled the detection of abnormal behavior, the interpretation of the anomaly together with machine experts allowed the identification of the degraded component, and the subsequent maintenance intervention successfully resolved the issue. The presented case study therefore illustrates how the proposed framework can transform process data into actionable maintenance decisions in a real industrial environment.

At the time of detection, no conventional indicators of degradation were present, such as an increase in reject rate or other performance metrics. Nevertheless, the signal exhibits a clear periodic pattern, which deviates from the expected stochastic behavior. This structured oscillation represents an early-stage degradation sign that is not captured by standard metrics, but may ultimately lead to performance deterioration or failure of the pin.

Following the proposed framework, the anomaly was dis-

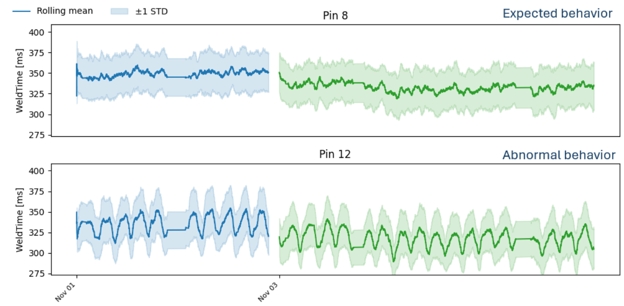

Figure 3. Comparison between expected and abnormal behavior. Colors indicate different production shifts.

cussed with the machine experts, which suggested a potential issue with the piston movement. A targeted inspection confirmed the piston as the root cause: it was found to be misaligned, leading to intermittent fluctuations in the welding time due to partial obstruction during its motion.

To validate this hypothesis, the piston was temporarily replaced. As shown in Fig. 4, the replacement took place between November 5 and November 13. During this period, a clear change in the welding time behavior is observed, consistent with the removal of the faulty component and its subsequent reinstallation. This intervention effectively acts as a controlled experiment, confirming the causal relationship between the observed oscillatory pattern and the piston misalignment. Following this validation, the piston was permanently replaced.

To capture and quantify the oscillatory behavior observed in the welding process, we introduce a rolling spectral indicator that measures the concentration of signal energy in the frequency domain. This characterization will also enable the automatic detection of such abnormal patterns in future operations.

4.1. Fast Fourier Transform (FFT) Peak Ratio

Before computing the FFT Peak Ratio, the production data were first sorted chronologically and divided into continuous production segments. A new segment was created whenever the time gap between two consecutive welding cycles exceeded two hours, ensuring that FFT windows were not computed across machine stops or prolonged production interruptions. Although the production data are not perfectly regularly sampled in time due to machine stops and process interruptions, no interpolation or resampling was applied. Instead, the segmentation strategy ensured that spectral analysis was only performed on locally continuous production periods, which were considered sufficiently quasi-stationary for the proposed monitoring approach.

Let $x(t)$ denote a discrete-time signal acquired from the pro-

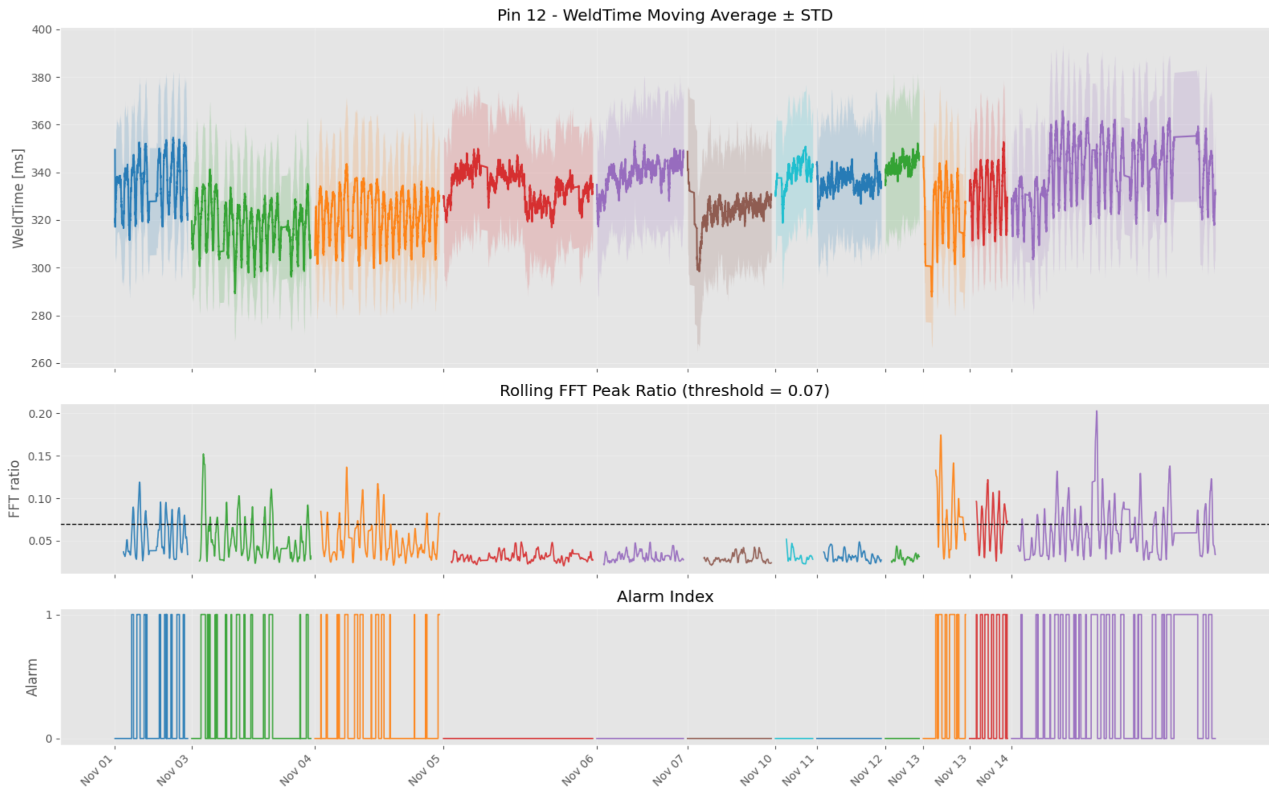

Figure 4. Results of the FFT peak ratio for detecting abnormal oscillatory behavior, along with the resulting threshold-based alarm. Each color represents a different working shift.

cess (e.g. the welding time), sampled at irregular or quasi-regular intervals and indexed by t_i, $i = 1, \dots, N$.

For each time index $i \geq W$, we consider a sliding window of length W:

$$\mathbf{w}_i = \{x_{i-W+1}, x_{i-W+2}, \dots, x_i\} \tag{1}$$

In the industrial pilot presented in this work, a window size of $W = 200$ welding cycles was used, with overlapping evaluations performed every 100 samples.

The windowed signal is then centered by removing its mean:

$$\tilde{w}_k = w_k - \mu_i, \quad \text{with} \quad \mu_i = \frac{1}{W}\sum_{k=1}^{W} w_k \tag{2}$$

and the power spectral density (PSD) of the centered signal $\tilde{\mathbf{w}}_i$ is estimated using Welch's method:

$$P_i(f) = \text{PSD}\left(\tilde{\mathbf{w}}_i\right) \tag{3}$$

where $\{P_i(f_j)\}_{j=1}^{M}$ denote the discrete PSD values over the frequency bins.

Finally we define the FFT Peak Ratio as the proportion of total spectral energy concentrated at the dominant frequency:

$$R_i = \frac{\max_j P_i(f_j)}{\sum_{j=1}^{M} P_i(f_j)} \tag{4}$$

This ratio takes values in $[0, 1]$ and provides a measure of spectral concentration. A low value of R_i indicates that the signal energy is distributed across multiple frequencies, which is typical of stochastic or non-periodic behavior. Conversely, a high value of R_i indicates that a significant portion of the signal energy is concentrated at a single frequency, revealing the presence of periodic or quasi-periodic dynamics.

To detect abnormal regimes, a binary alarm index is defined based on a threshold τ:

$$A_i = \begin{cases} 1 & \text{if } R_i > \tau \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

The threshold τ was calibrated using historical data collected during known healthy operating conditions. In particular, a healthy reference dataset was constructed by selecting production periods where the reject rate remained below 0.5% for each individual pin. The FFT Peak Ratio R_i was then computed over these healthy operating periods across multiple pins. To limit the occurrence of false alarms while preserving sensitivity to abnormal oscillatory behaviors, the threshold τ was defined as:

$$\tau = 1.2 \times P_{99}(R_i)$$

where $P_{99}(R_i)$ denotes the 99^{th} percentile of the FFT Peak Ratio distribution under healthy operating conditions. The multiplicative factor of 1.2 was introduced as a safety margin to reduce the sensitivity of the alarm system to normal process variability and avoid excessive false positive detections. The result for this application is a value of $\tau = 0.07$

The proposed indicator captures changes in the spectral structure of the signal rather than its amplitude or mean value. It is therefore particularly suited to detecting the onset of structured oscillations, which may be associated with mechanical instabilities, resonance phenomena, or degradation mechanisms in the welding system.

Fig. 4 illustrates the application of the proposed indicator and the resulting alarm signal for the case study. By selecting a threshold τ calibrated across all pins to account for their different nominal behaviors, the method effectively discriminates between distinct operating regimes.

The indicator clearly highlights the presence of oscillatory behavior in the early stage (November 1–4), followed by a stable regime after the piston replacement (November 5–12), and the reappearance of abnormal dynamics when the faulty component is reinstalled (November 13–15). These transitions are consistently captured by the threshold-based alarm, which activates only during periods characterized by strong spectral concentration. Quantitatively, the average FFT Peak Ratio of Pin 12 during the initial abnormal phase was equal to 0.0522, with 23% of the analyzed windows exceeding the alarm threshold. During the intermediate phase, where the piston was removed and replaced, the average FFT Peak Ratio decreased to 0.03, while no alarm activation was observed. Finally, during the last phase, when the defective piston was intentionally reinstalled to validate the hypothesis, the average FFT Peak Ratio increased again to 0.063, with 44% of the windows triggering the alarm condition.

To further support the validity of the proposed indicator, a comparison was performed with other healthy pins operating during the same production period. For example, Pin 1 presented an average FFT Peak Ratio of 0.03 with no alarm activations over the complete timeframe, while Pin 10 showed an average FFT Peak Ratio of 0.031 with only 0.35% of alarm activations. These results confirm that the observed oscillatory behavior was localized and not representative of the nominal machine behavior.

This demonstrates that the proposed approach enables reliable and timely detection of abnormal periodic patterns, allowing operators to intervene at an early stage, before such behaviors impact machine performance or lead to component failure.

5. CONCLUSION

This work presents an industrial application of the proposed PHM framework for the early detection and diagnosis of abnormal behaviors in ultrasonic welding systems. Through a real industrial use case, we showed how a previously undetectable anomaly, characterized by a structured oscillatory pattern, could be identified directly from process data before being visible through conventional indicators such as reject rate.

The presented case study illustrates how the proposed monitoring approach can support an actionable workflow, from anomaly detection to root cause analysis and maintenance intervention. In particular, the FFT Peak Ratio indicator enabled the identification of abnormal operating regimes, while the integration of expert knowledge supported the interpretation of the detected patterns and the identification of the degraded component. The successful maintenance intervention following the analysis provides promising industrial evidence of the practical relevance of the proposed methodology.

Furthermore, this work highlights the potential of combining data-driven monitoring and expert-driven interpretation for the progressive construction of a knowledge base linking observed anomalies to their corresponding root causes and corrective actions. Such an approach may support more systematic maintenance decision-making processes in industrial environments.

Nevertheless, the current validation remains limited to a single industrial use case associated with piston misalignment in one machine configuration. Additional validation across multiple machines, degradation mechanisms, and longer operating periods will therefore be necessary to further assess the generalization capability and robustness of the proposed framework. In addition, the threshold calibration currently relies on empirically defined healthy operating periods and may require adaptation under changing production conditions or machine configurations.

Future work will focus on extending the framework along three main directions. First, the development of a structured historical repository of anomalies and failure modes will enable the detection and classification of a broader range of abnormal behaviors. Second, the integration of large language models (LLM) within the framework will allow leveraging this knowledge base to automatically match newly detected anomalies with previously observed cases, thereby improving diagnostic efficiency. Finally, the accumulation of historical degradation data may support the transition from anomaly detection toward prognostics and remaining useful life estimation of critical components.

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