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Advanced Validation Methodology for KPI-Based Robotic Condition Monitoring in an Industry 4.0 Framework

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***Abstract* – In this work, a methodology is presented for the advanced validation of KPI-based condition monitoring systems applied to industrial robotics. The proposed approach is demonstrated through a test case involving an industrial robotic arm equipped with ICP accelerometers for high-fidelity vibration measurements. The acquired signals are collected by a high-speed DAQ system and processed in real time on a Raspberry Pi used as an edge computing device. Digital signal processing techniques, including filtering, spectral analysis, Fast Fourier Transform, and statistical feature extraction, are applied to generate health-related KPIs associated with robotic joint conditions. The validation methodology assesses sensor reliability, signal processing robustness, KPI sensitivity, repeatability, false alarm rate, and diagnostic capability. The extracted indicators are transmitted via MQTT to an IIoT platform for remote monitoring, historical analysis, and maintenance alert generation. The test case aims at demonstrating the effectiveness of the methodology for early fault detection and predictive maintenance in Industry 4.0 environments.**

***Keywords* – Validation, Condition Monitoring, Robotic Arm, Industry, Innovation and Infrastructure.**

I. INTRODUCTION

In 2024, more than 500,000 industrial robots were sold worldwide and more than 4.6 million were in operation worldwide, representing a 9% increase from 2023. Industrial robots are ubiquitous in industrial manufacturing, where they are used for tasks such as material handling, assembly, and machining [1].

Industrial robots are frequently used in hard-to-reach areas of production lines. To ensure they can perform their tasks without fail, their components must be precisely calibrated and in good working condition. Since the components are subjected to stress with every work cycle, they are subject to wear and tear, which can lead to unplanned downtime and result in the shutdown of an entire production line. Automated, continuous condition monitoring of industrial robots is therefore an effective way to prevent production downtime while reducing non-productive time caused by manual inspections [2].

The condition monitoring and fault diagnosis of industrial robots generally take place at the system and component levels, with model-based methods dominating at the system level, while at the component level, data-driven approaches are increasingly being used based on log data, sensor data from sensors already present in the robot for control purposes, and additional sensors such as accelerometers, current sensors, and IMUs. Model-based methods utilize analytical redundancy and include parameter identification, parity space methods, and state estimation techniques; however, they face the challenge of accurately modeling the nonlinear dynamic properties of industrial robots, such as friction, backlash, and elasticity. Data-driven methods, most of which have only been developed in the last five years, benefit from advances in deep learning but suffer from a lack of robot-specific error datasets, a reliance on defined motion trajectories, and time-varying operating conditions that make robust feature extraction difficult. Furthermore, the limited sensor equipment on many industrial robots significantly restricts the diagnostic capabilities of mechanical components [3].

The increasing adoption of industrial robotic systems in advanced manufacturing environments has intensified the need for reliable, real-time, and data-driven condition monitoring solutions. Industrial robotic arms operate under repetitive, high-duty-cycle conditions, where joint wear, backlash, bearing degradation, lubrication issues, misalignment, and incipient mechanical faults can progressively affect motion accuracy, productivity, and operational safety. Within this context, predictive maintenance represents a key enabling strategy of Industry 4.0, allowing maintenance actions to be scheduled according to the actual health condition of the asset rather than fixed time intervals or reactive interventions after failure occurrence. The present case study focuses on the development and validation of an intelligent condition monitoring system for an industrial robotic arm, with particular attention to the methodological framework adopted to assess the reliability, robustness, and diagnostic effectiveness of the generated health indicators.

II. MATERIALS AND METHODS

The proposed system is designed to continuously monitor the vibrational behaviour of robotic joints and to extract meaningful Key Performance Indicators (KPIs) capable of describing the evolution of the mechanical condition of the robot over time.

Vibration-based monitoring was selected as the primary diagnostic approach because mechanical degradation phenomena in rotating components, gear transmissions, reducers, bearings, and articulated joints often manifest themselves through changes in amplitude, frequency content, impulsiveness, and statistical distribution of vibration signals. For this purpose, high-performance ICP accelerometers are adopted, specifically PCB PIEZOTRONICS model 352A24 sensors, characterized by a sensitivity of 100 mV/g and a measurement range of ±50 g peak.

The accelerometers were integrated with a high-speed data acquisition architecture based on a Digilent MCC 172 IEPE Measurement DAQ HAT mounted on a Raspberry Pi 4 platform. The DAQ system allows vibration signals to be sampled at up to 51.2 kS/s, a sampling frequency adequate for capturing both low-frequency structural dynamics and high-frequency transient components typically associated with impact events, local defects, or abnormal joint behaviour. The Raspberry Pi 4 Model B acts as the edge computing unit, performing local signal processing directly close to the monitored asset. This edge-based architecture minimizes latency, reduces the volume of transmitted data, and enables real-time or near-real-time anomaly detection without requiring the continuous upload of raw high-frequency vibration signals to a remote cloud infrastructure. The raw vibration signals acquired from the robotic joints are processed through a sequence of digital signal processing operations. First, signal conditioning and filtering are applied to remove noise, unwanted components, and possible acquisition artefacts. Then, time-domain, frequency-domain, and statistical analyses are performed. In the time domain, indicators such as root mean square value, peak value, peak-to-peak amplitude, crest factor, skewness, kurtosis, and variance are extracted In the frequency domain, spectral analysis based on the Fast Fourier Transform is used to identify changes in dominant frequencies, broadband energy, and possible fault-related components.

Additional KPIs may include band-limited energy, spectral centroid, spectral entropy, harmonic distortion measures, and envelope-based indicators, depending on the specific fault signatures of interest. These KPIs provide a compact representation of the health state of each monitored joint and constitute the basis for subsequent diagnostic and prognostic evaluation.

III. EXPERIMENTAL SETUP

The experimental setup uses a 6-axis industrial robot from MABI Robotic AG, model MAX-100-2.25-Precision, equipped with a CNC controller from Siemens AG, model Sinumerik ONE NCU 1760 with PLC 1500F. The axis ranges and angular velocities for axes A1 to A6 can be found in Table 1.

Table 1. Range and speed of the MABI robot MAX-100-2.25-Precision.

Axis	Range	Speed
A1	± 181°	75°/s
A2	[+ 138°; - 73°]	45°/s
A3	[+ 73°; - 178°]	95°/s
A4	± 300°	130°/s
A5	± 95°	75°/s
A6	± 181°	170°/s

The robot is equipped with a miniaturized acceleration sensor from PCB Piezotronics, Inc., Model 352A24 in each of the gearboxes for axes A1 through A4 for the condition monitoring system to detect wear. The sensor has a sensitivity of 100 mV/g and a frequency range of 1 to 8 kHz. High-frequency acquisition of drive data is also possible using the control system's trace function. In addition, the robot control system includes an OPC UA server, which provides access to a wide range of parameters and variables such as speed and axis position in an Industry 4.0 environment.

Predefined self-tests for assessing the condition of robot joint axes are an approach in which constant boundary conditions are specified to make data analysis more robust against unknown disturbances. In the self-test for robot axes developed at Fraunhofer IPK, the axes to be monitored move sequentially from a defined starting position across the maximum available working range, in both the positive and negative directions at a constant angular velocity. During the test, measurement parameters are recorded, and conclusions about the wear condition of the robot axis can be drawn from their characteristic curves [2].

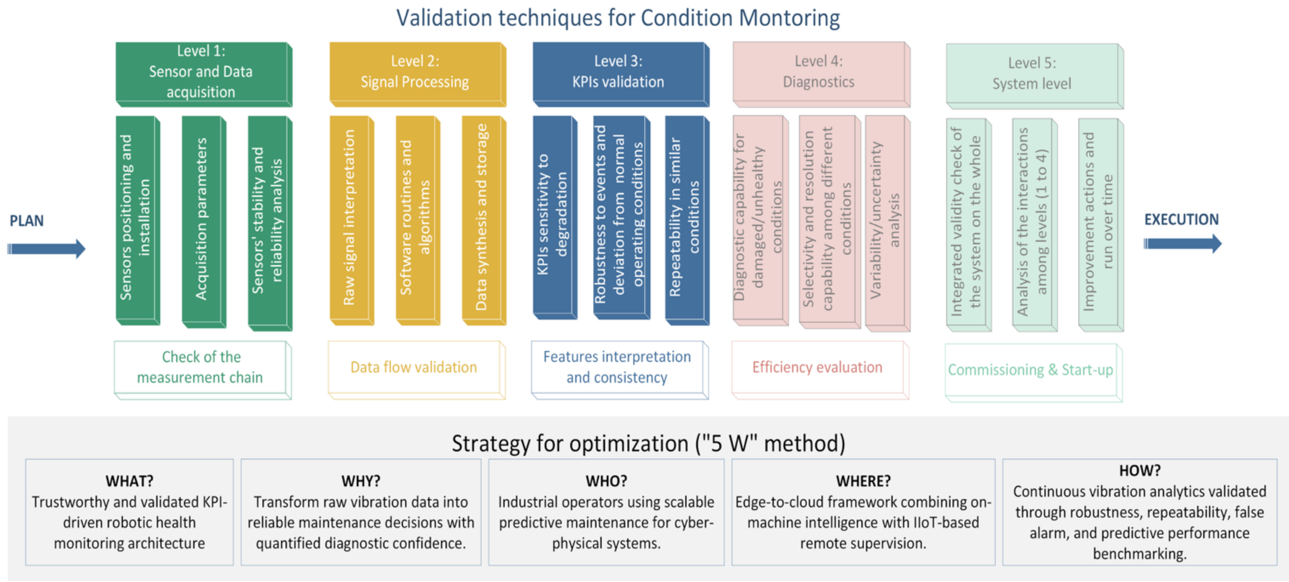

Fig. 1. Validation Techniques for condition monitoring of the robotic system and strategy for optimization

IV. VALIDATION TECHNIQUES

A central contribution of this work is the definition of an advanced validation methodology for KPI-based robotic condition monitoring.

Since condition monitoring systems are intended to support maintenance decisions in operational environments, the validation process cannot be limited to verifying the correct acquisition of sensor data or the proper implementation of signal processing routines. Instead, it must assess whether the selected KPIs are truly sensitive to degradation, robust to normal operating variability, repeatable under comparable conditions, and effective in discriminating between healthy and faulty states.

The validation methodology is therefore structured around several complementary levels as reported in the following subsections: sensor and acquisition validation, signal processing validation, KPI validation, diagnostic validation, and system-level validation.

A. Sensors and acquisition validation

At the first level, sensor and acquisition validation ensures that the measurement chain is suitable for the intended application. This includes verifying accelerometer placement, mechanical coupling, signal quality, sampling rate adequacy, and synchronization among acquisition channels The selected sampling frequency of 51.2 kS/s is assessed with respect to the expected frequency content of robotic joint vibrations and to the requirements of fault detection in rotating and articulated mechanical systems.

Further validation techniques involve the evaluation of the signal-to-noise ratio, repeatability of acquisitions, and sensitivity check to correctly interpret the measurement signals as mechanical degradation of the artifact within the limits of its signature variability.

B. Signal processing validation

At the second level, signal processing validation focuses on the correctness and stability of the algorithms implemented at the edge.

Filtering procedures are implemented to ensure that diagnostically relevant frequency components are preserved, while irrelevant noise contributions are attenuated. The implementation of spectral analysis, statistical feature extraction, and KPI computation can be verified using known reference signals, repeatability tests, and controlled operating cycles of the robot.

This stage is essential because errors or instabilities in edge processing may propagate to the IIoT platform and compromise the reliability of subsequent maintenance decisions.

C. KPI validation

The third level concerns KPI validation, which is the core of the proposed methodology. Each KPI is evaluated according to its sensitivity to mechanical condition changes, robustness to nominal operating variability, and interpretability for maintenance personnel.

Sensitivity analysis is performed by comparing KPI distributions under different operating states, including healthy baseline conditions and altered or degraded configurations when available.

Statistical features such as variance ratio, confidence intervals, and separability indices can be used to quantify the capability of each KPI to distinguish between normal and abnormal conditions. Robustness is assessed by analysing KPI stability across repeated robot cycles, different payloads, velocities, trajectories, and environmental conditions. A KPI suitable for predictive maintenance should not generate significant fluctuations under normal operational variability, while still reacting clearly to actual degradation phenomena.

D. Diagnostics validation

The fourth level addresses diagnostic validation through benchmarking against alternative condition assessment methods, such as statistical thresholds, unsupervised anomaly detection, supervised machine learning, or hybrid diagnostic models. This comparison enables the monitoring system to be evaluated in terms of false alarm rate, missed detections and detection delay to improve the predictive capability. Particular attention is given to balancing early fault detection with alarm reliability, since excessive false alarms may reduce operator trust, while missed detections may lead to failures and downtime.

Cross-validation is adopted to assess generalization capability. When labelled data are available, they are divided into training, validation, and test sets. When fault data are scarce, validation can rely on repeated healthy-state measurements, controlled perturbations, historical data, or physics-informed assumptions, for example from a digital twin. Multiple validation scenarios improve reliability and reduce overfitting to specific operating conditions.

E. System level validation

At the system level, extracted KPIs and health indicators are transmitted to an IIoT platform via MQTT, enabling remote monitoring, historical data storage, dashboard visualization, and alert generation. This allows robotic joint health to be tracked over time and supports data-driven maintenance scheduling. Validation at this level concerns not only KPI diagnostic quality, but also transmission reliability, latency, data completeness, and usability for operators. The combination of edge computing and cloud monitoring provides a balance between local responsiveness and long-term analytics. The methodology also considers KPI temporal behaviour, since predictive maintenance requires detecting degradation trends before functional failure. Trend analysis, moving statistics, control charts, and degradation-rate estimation can support this task, in order to provide valuable KPIs able to show a progressive, interpretable evolution correlated with component deterioration.

V. PRELIMINARY EXPERIMENTAL VERIFICATION

Before applying the proposed validation methodology to degradation scenarios, preliminary activities were carried out to verify the measurement chain and to define repeatable robot operating conditions. These tests address two effects that could otherwise be confused with changes in mechanical condition: errors introduced by acquisition or processing and variability associated with trajectory, joint speed, and sampling configuration.

A. Acquisition-chain and algorithm verification

The acquisition board and edge-processing routines were first tested independently of the robot. A programmable signal generator was connected to the MCC 172 input and periodic signals with known amplitude and frequency were supplied over the range relevant to the subsequent vibration tests. Each waveform was acquired using the same channel configuration, sample-buffer management, time-vector generation, and data-transfer routines planned for the robotic experiments. The acquired records were analysed through a classical least-squares sinusoidal fit, $x(t_i) = A \sin(2\pi f t_i + \varphi) + c + \varepsilon_i$, where A, f, φ, and c denote amplitude, frequency, phase, and offset, respectively, while ε_i is the fitting residual.

The fitted parameters were compared with the generator settings, while the residual root-mean-square value and the relative errors in amplitude and frequency were used to identify possible gain, time-base, offset, clipping, or implementation errors. Repetition across channels and sampling settings also provided a check of channel consistency and algorithm stability. This controlled test separates acquisition and processing effects from the mechanical variability of the robot and provides the functional verification required before KPI extraction.

B. Definition of the robot working envelope

Before repeated vibration acquisitions, the robot working envelope and the reference self-test trajectory were preliminarily tuned. The start and end positions were selected to exploit a sufficiently wide joint stroke while avoiding mechanical limits, singular configurations, interference with surrounding equipment, and excessive loading of sensor cables. The programmed profile includes acceleration and deceleration phases and a central interval at approximately constant angular velocity. For comparable KPI evaluation, the same motion phase, direction, payload, and initial configuration must be retained in every test; transient portions may instead be analysed separately when impact or backlash-related information is of interest.

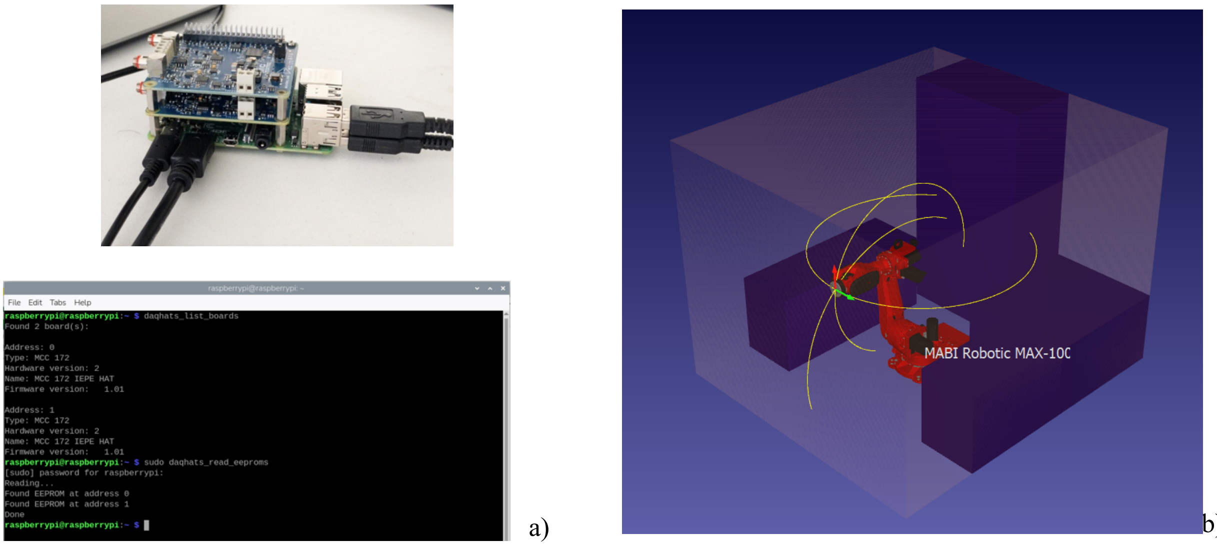

Fig. 2. Preliminary experimental preparation: (a) verification of the MCC 172/Raspberry Pi acquisition and fitting algorithms using a signal generator; (b) tuning of the robot working envelope and reference trajectory.

C. Acquisitions at different sampling rates and joint speeds

A preliminary acquisition plan based on three sampling frequencies and three angular velocities of the monitored joint was considered as part of the validation methodology at the acquisition and signal-processing levels. The comparison among these operating conditions is relevant not only for describing the acquired signals, but also for verifying whether the measurement chain and the extracted indicators remain consistent when the acquisition settings and robot dynamics change. Time-domain statistical descriptors, supported where available by normalized histograms, allow differences in signal offset, dispersion, symmetry, tail behaviour, and outliers to be assessed. For a meaningful comparison, common amplitude limits and bin edges, together with normalized counts or probability density, are required to avoid apparent differences caused only by the different numbers of samples associated with the selected sampling frequencies.

Within this validation framework, the effects of joint speed and sampling frequency must be distinguished. An increase in angular velocity may produce broader distributions or more pronounced tails as a consequence of higher dynamic excitation. On the other hand, when sensor bandwidth, anti-aliasing filtering, and signal conditioning are adequate, the sampling frequency should not systematically modify the underlying amplitude distribution.

Variations associated with the sampling rate may therefore indicate unwanted effects such as aliasing, filtering or synchronization issues and represent a useful evidence for assessing the robustness of the measurement acquisition and processing chain. Since time-domain distributions do not describe how signal energy is splitted across frequency, the validation also included a comparison between the amplitude spectra acquired with the robot switched off and with the monitored axis in motion. In the stationary condition, only low-level harmonic components were observed, whereas axis motion produced a dominant fundamental component, a higher broadband noise floor, and additional harmonics that were not distinguishable in the stationary spectrum (Fig. 3.). This combined analysis is essential for identifying a sampling rate that preserves the relevant KPIs and spectral content while avoiding unnecessary computational and data-transmission burdens.

No artificial fault condition was introduced at this stage. For this reason, the results are interpreted as evidence of measurement consistency, repeatability under controlled conditions, and sensitivity to operating parameters, rather than as a demonstration of diagnostic accuracy. Nevertheless, these aspects realize a necessary validation step, since the reliability of the next fault detection depends on the ability to distinguish changes due to degradation from variations induced by acquisition settings or normal robot operation.

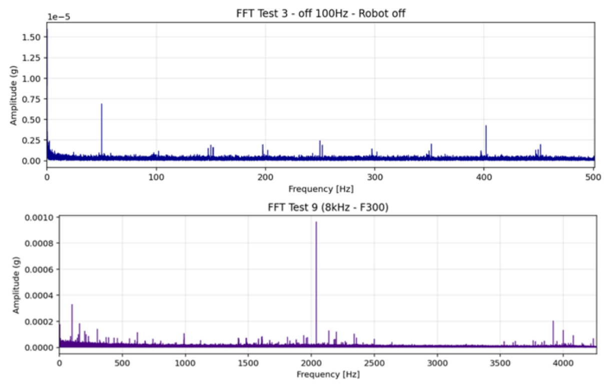

Fig. 3. Comparison of the amplitude spectra acquired with the robot switched off and with the monitored axis in motion

VI. DISCUSSION

The work aims at demonstrating that the combination of high-fidelity vibration sensors, high-speed data acquisition, edge computing, and IIoT connectivity provides a technically sound architecture for robotic condition monitoring. Its added value lies in the rigorous validation of the generated KPIs and diagnostic outputs by assessing sensitivity, robustness, repeatability, false alarm rate, and predictive capability. This is particularly important in robotic systems, where operational variability may affect productivity, safety, and asset availability.

The initial phase requires the identification of robot fine-tuning routines and the selection of suitable speeds, trajectories, and parameter settings to establish reliable operational references. This preliminary validation activity is fundamental because the resulting signatures and benchmarks may strongly depend on these conditions. A second operational level concerns the definition of the analysis boundaries and monitoring system requirements, including the use of historical data and simulated trajectories.

The preliminary activities reported in Section V implement the first phase of the validation strategy. Controlled-input tests verify the acquisition and fitting chain, while workspace tuning establishes repeatable boundary conditions for the robotic self-test. Sampling frequency and joint speed are also treated as controlled factors when defining baseline signatures. Although these results do not yet constitute diagnostic validation, since no controlled fault state has been introduced, they establish the measurement and operational prerequisites for subsequent KPI sensitivity, robustness, and repeatability studies.

VII. CONCLUSIONS

In conclusion, the developed robotic condition monitoring system supports the early detection of joint degradation and mechanical anomalies through continuous vibration monitoring and real-time KPI extraction.

The edge-based implementation reduces data transmission requirements and enables immediate processing close to the machine, while the IIoT platform provides remote access, historical analysis, and alert management. A first controlled verification using generated reference signals, together with workspace tuning and acquisitions at different sampling rates and joint velocities, supports the suitability of the measurement chain and defines repeatable baseline conditions for the subsequent diagnostic campaign.

The advanced validation methodology proposed in this case study ensures that the monitoring framework is not only technically functional, but also diagnostically reliable and industrially meaningful. Through benchmarking against alternative statistical and machine learning-based diagnostic tools, the system can be quantitatively evaluated and progressively improved. This approach contributes to the development of trustworthy KPI-based health monitoring solutions for industrial robots and supports the broader implementation of predictive maintenance strategies within Industry 4.0 manufacturing environments.

Future work will define the analysis boundaries and monitoring-system requirements more formally. Repeated healthy-state cycles, historical data, and simulated trajectories will be combined with controlled perturbations, when available, to quantify within-condition variability, separability among operating states, and the uncertainty associated with each KPI.

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