BULLETIN OF THE POLISH ACADEMY OF SCIENCES
TECHNICAL SCIENCES, Vol. 73(6), 2025, Article number: e155042
DOI: 10.24425/bpasts.2025.155042

CONTROL, INFORMATICS AND ROBOTICS

Condition monitoring of pick-and-place robots using IIoT-based data acquisition systems

Marcin KORZENIOWSKI* and **Bartosz TARKOWSKI**

Wrocław University of Science and Technology, Wrocław, Poland

Abstract. Modern industry challenges companies to ensure high reliability of machinery and equipment and continuity of production processes. An important role in this is played by condition monitoring of machines, during which the operating parameters of the equipment are analyzed, assessing its condition and the degree of wear of components. As part of ongoing research, an IIoT (Industrial Internet of Things)-based solution was developed to monitor the condition of the joints of a FANUC M-1iA/1H industrial robot. The project involved the integration of sensors on the axes of the robot performing the pick and place process. A set of condition monitoring tools – CMTK – and sensors enabling diagnostics were used to collect and visualize data. The monitoring system is based on the analysis of such parameters as the speed of vibration of the joints, their temperature and the number of cycles performed by the robot. The data sent to the CMTK unit are processed and visualized in the Grafana environment, making it possible to track the state of the machine in real time. Tests conducted showed the cyclicity of vibrations during the robot's operation. A clear correlation was observed between the speed of the manipulator's movement and the vibration level – the highest values were recorded at 4000 mm/s, especially during the braking phase. Deviations from the established pattern can indicate potential failures. The test results confirm the effectiveness of the applied solution as a diagnostic tool ready for industrial deployment. Despite the initial cost, the implemented solution increases production efficiency by reducing downtime and enabling preventive component replacement.

Keywords: condition monitoring; parallel robot; palletization process; pick & place process; Industrial Internet of Things; vibration measurements.

1. INTRODUCTION

Condition monitoring of machines and civil engineering construction is currently one of the applications of IIoT (Industrial Internet of Things) technology. It involves continuous tracking of specific machine operating parameters (e.g. vibration), which allows for ongoing assessment of its technical condition and the degree of wear and tear of individual components. This makes it possible to determine when a component needs to be replaced before it fails, which could result in production stoppages for a long period of time [1]. There can be many monitored parameters, e.g. temperature, ultrasonic vibrations, lubricant contamination, electrical parameters. However, the most important and most frequently used method is the analysis of the vibration of individual components performed by H.A. Raja *et al*. [2], S.S. Saidin *et al*. [3] and T. Singh *et al*. [4]. A running machine generates vibrations that provide a lot of information about its condition. Machine vibrations can have a significant impact on building construction, particularly in structures near industrial or heavy machinery operations. Over time, vibrations from machines, such as those from robotic systems, construction equipment, or manufacturing machinery, can lead to structural damage, including cracks in walls, floors and foundations. Constant vibration can weaken integrity of the building materials, affecting the long-term stability and safety of the construction. Additionally, vibrations can interfere with sensitive equipment or delicate processes inside buildings, such as in laboratories or offices. Therefore, monitoring and controlling vibrations is critical in construction environments to prevent damage, ensure safety and maintain durability of the structure. In article [5], the authors proposed a methodology for the classification of robot collisions. This methodology involves the analysis of motor current and robot link vibrations through the utilization of variational mode decomposition (VMD) and an equivalent filter bank. The purpose of this analysis is to extract vibration features in an efficient manner. Subsequent to this, a neural network is trained to detect and classify collisions involving different materials, achieving high accuracy in distinguishing human-involved collisions and identifying the collision location. In a separate study, Nentwich and Reinhard [6] described a methodology for developing an effective data acquisition strategy for predictive maintenance of industrial robots. The authors emphasized the strategy's impact on productivity and cost reduction. The methodology is defined by several key aspects, including the components of the robot that are to be monitored, the trajectories for data collection, and the frequency at which measurements are to be taken. The limitations of the methodology are also addressed. The rapid advancement of IoT technologies has enabled improved machine interaction, facilitating not only control but also fault detection and predictive maintenance. The study conducted by H.A. Raja *et al*. [7] explores how IoT can enhance industrial diagnostics, addressing the need for cost-effective and time-efficient maintenance solutions. Robot condition monitoring is essential for maintaining production

*e-mail: marcin.korzeniowski@pwr.edu.pl

Manuscript submitted 2025-04-02, revised 2025-07-26, initially accepted for publication 2025-07-31, published in November 2025.

efficiency, but the dynamic working states of industrial robots pose significant challenges. Paper [8] proposes a vibration-based methodology using frequency response analysis and short-time Fourier transform to detect faults and assess their severity in industrial robots. Predictive maintenance strategies that utilize vibration-based condition monitoring have been shown to play a crucial role in preventing unexpected breakdowns of heavy machinery. A study conducted by U. Hassan *et al*. reviewed various data collection methods [9], evaluating different accelerometers and their effectiveness in measuring vibrations for improved maintenance efficiency. The research described in [10] introduces an online process monitoring method that utilizes a vibration-surface quality map and a convolutional neural network classifier to detect grinding states, enhancing real-time quality control in robotic machining. In a related study, H. Han *et al*. proposed a vibration-based monitoring approach that uses a triaxial MEMS accelerometer to detect faults and analyze the vibration characteristics of different robot joints [11]. This demonstrates the feasibility of this method for fault detection and severity assessment. Effective tool condition monitoring is essential for maintaining process performance in robot-based incremental sheet forming. In a subsequent paper [12], the authors demonstrated the use of vibration signal analysis with an accelerometer sensor to assess tool wear and surface roughness, highlighting the correlation between increased vibration and deteriorating tool condition. The authors of [13] developed an equipment condition monitoring system based on LabVIEW using the UDP communication protocol, dynamic invocation and reentrant technology. The experimental results confirm the system's ability to efficiently display, store and analyze data in both the time and frequency domains. This supports fault diagnosis, accident prevention and improved production efficiency. In a subsequent article [14], the authors introduce a wireless monitoring system for operational modal analysis of bridges, using MEMS accelerometers and a low-power Wi-Fi module for long-term data collection. The system has been shown to successfully address challenges such as data synchronization and preprocessing, as evidenced by experimental validation and real-world deployment on a concrete arch bridge. R.J. Stephen *et al*. explored a tool condition monitoring approach for drilling operations using an accelerometer sensor to analyze vibration signals in both time and frequency domains [15]. By utilizing LabVIEW for vibration amplitude prediction and training ANN, fuzzy neural networks and Taguchi models with experimental data, the methodology effectively detects tool wear and optimizes machining conditions. A study performed by X. Zhao *et al*. proposes a force and material removal monitoring method for robotic grinding based on acceleration signals [16]. By utilizing an LSTM network to model the vibration-force relationship, the framework enables real-time estimation of grinding force and material removal, ensuring machining quality. H. Badkoobehhezaveh *et al*. analyzed the dynamic and vibration characteristics of a newly developed 5-DOF long-reach robotic arm for farm applications using both finite element analysis (FEA) and experimental modal analysis [17]. The verified FEA model, which demonstrated good agreement with experimental results, provides a foundation for future vibration control and performance optimization under base excitation. A paper developed by Halder and Asfari [18] analyzed many robotic solutions for inspection and monitoring of the built environment, identifying nine types of robotic systems, with UAVs and UGVs being the most common ones. The study highlights key research areas such as autonomous navigation, sensing, and multi-robot collaboration, offering insights for future developments in robotic inspection technologies. Advancements in robot control, emphasizing model-based control, multi-robot coordination, force control and wireless communication, used to enhance performance and reduce costs, have been described in detail in [19]. Future trends include lightweight modular robots, adaptive control for optimized performance, and expanded applications in industries such as the automotive and food processing ones, as well as in small and medium enterprises. In their study, Nentwitch and Daub examined sensor selection for industrial robot gear condition monitoring, comparing current and vibration sensor data in accelerated wear tests [20].

The findings emphasize the significance of sensor characteristics and frequency range variations in the effective detection of faults. Furthermore, Yuan *et al*. have developed a vision-based method for assessing cracks in reinforced concrete structures, utilizing an inspection robot equipped with a stereo camera and the IoT for data communication [21]. The method employs deep learning for crack quantification and projects damage information with 3D reconstruction of the structure, demonstrating high accuracy in damage segmentation, localization and quantification during validation experiments. A dynamic model for robot transmission defect detection, specifically targeting gear faults, by developing a geometric model based on the modified Denavit-Hartenberg approach and applying the Euler-Lagrange convention, is presented in [22]. The effectiveness of the model is validated through numerical simulations and experimental vibration analysis, demonstrating its capability to detect gear defects under different conditions. Han *et al*. proposed a condition monitoring method for industrial robots using vibration analysis based on data from a triaxial MEMS accelerometer [23]. Their experimental results demonstrated that vibration characteristics vary across different robot joints, and that fault location and severity – such as seal ring defects – can be effectively identified using frequency and time-domain analysis.

A comprehensive review of the literature reveals the paramount importance of condition monitoring for robots and machines. This approach enables early detection of defects, including gear faults, which can have a substantial impact on product quality and also result in financial losses. The literature survey indicates that robotic components that are subject to continuous monitoring will experience a reduction in unplanned downtime, an enhancement in operational efficiency, and an increase in the lifespan of the machinery. This, in turn, will ensure consistent performance and the production of goods and services of consistently high quality. Beyond serving as a diagnostic tool, condition monitoring systems have the potential to support broader digital transformation initiatives within industrial environments. The continuous collection and analysis of data from the robot's joints – such as vibration velocity, temperature and operational cycles – can serve as a data source for digital twin models, allowing real-time simulation and predictive modeling of robotic behavior. Furthermore, integration with AI-driven diagnostic algorithms could enhance the system's ability to detect subtle deviations and forecast failures, and to then recommend maintenance actions autonomously. These capabilities directly contribute to resilience against production losses, as they enable early detection of wear, minimize unplanned downtime, and support proactive decision-making in maintenance planning. This enables not only localized diagnostics but also scalable, intelligent maintenance ecosystems aligned with Industry 4.0 principles.

2. METHODOLOGY

2.1. Condition monitoring

Vibration velocity is recorded by sensors, usually based on accelerometers, which then send the individual values to a master device capable of processing such large amounts of data. The sensors are usually attached to the housing of the machine to be monitored. The vibrations recorded by the sensor are called vibration signals, which can occur in the time domain or in the frequency domain [1]. Transition between these two domains is made possible by the Fourier transformation. The data collection rate, i.e. the sampling rate of this signal, depends on the quality of the specific sensor. The vibration signal is analyzed in detail to identify characteristic frequencies that can be used to detect different types of faults. The most common faults diagnosed include bearing and gear damage, which are characterized by higher frequencies, and problems such as imbalance, misalignment or looseness between components, which are characteristic of lower frequencies. An example of this is a defective roller bearing that emits vibrations at specific frequencies. The more intense these vibrations are, the more severe the damage. If the monitored process is repeatable to a certain extent, the same cycles can be compared at different time intervals and the differences analyzed, which can also indicate damage [1]. Condition monitoring is a technology that involves high initial costs, including the purchase of sensors and data processing equipment. However, in the long run, it saves money on periodic maintenance and unplanned downtime, and reduces the risk of misdiagnosis regarding component replacement. All in all, this technology becomes more effective, reliable and cheaper over time. Vibration diagnostics is an extremely complex issue that requires extensive knowledge and vast experience. Due to the variety of machine designs, consisting of different mechanical components and different operating conditions, each device requires an individual approach to the analysis and interpretation of the data collected [1].

2.2. Balluff BCM0002 condition monitoring sensors

For velocity measurements a Balluff BCM0002 condition monitoring sensor was used. The device measures vibration, surface temperature, ambient pressure and relative humidity. The sensor allows thresholds to be set for these parameters, and exceeding the set limits can be automatically detected and signaled. In addition, the device allows for a delayed response to events – the alarm is only triggered after a user-specified period of time during which the parameters remain outside the acceptable range, as shown in Fig. 1.

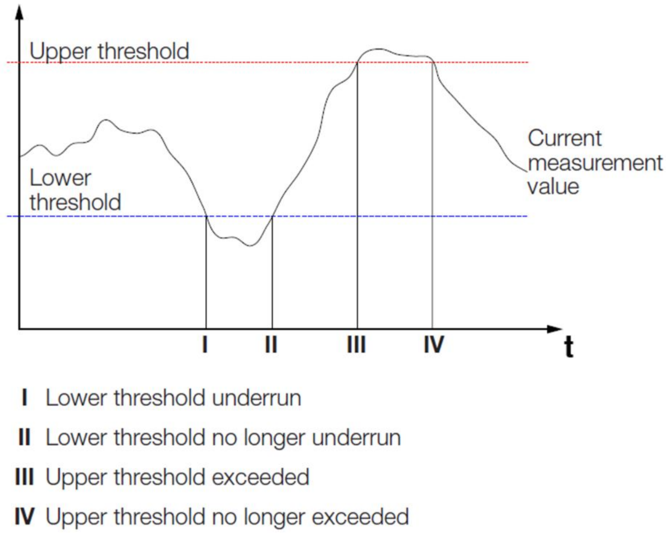

Fig. 1. Thresholding measured signals [24]

BCM0002 calculates the vibration velocity in three axes (X, Y and Z), based on the measured acceleration values. For each axis and in a specific time window, it stores parameters such as: average value, RMS (root mean square) value, standard deviation, skew coefficient and kurtosis. It also allows for the suppression of signals with frequencies outside the defined band, using a band-pass filter. BCM0002 also offers additional functions, such as an operating hours counter: since the last start-up, production run or since the last reset. The device is based on MEMS (micro-electro mechanical systems) technology, which enables the production of microscopic devices combining mechanical and electronic components. The data recorded by the sensor are sent to the master device via the IO-Link protocol. The BCM0002 sensor is capable of measuring vibration velocity of up to 12500 mm/s. It operates with an accuracy better than ±10% within the frequency range of 2 Hz to 1800 Hz, and extends up to 2500 Hz in an expanded range with a 3 dB tolerance. Vibration analysis is carried out within the defined time windows, during which the sensor calculates and provides statistical parameters. The time window must be selected manually by the user. A key principle applies: the lower the frequency to be analyzed, the longer the time window should be. The shortest available window is 20 ms, suitable for a minimum frequency of 100 Hz, while the longest is 1000 ms, allowing for the analysis of signals starting from 2 Hz [24]. Figure 2 shows the BCM0002 sensor coupled with one of the robot axes.

2.3. Condition monitoring toolkit (CMTK)

CMTK (BAV002N) is a toolkit for condition monitoring. This solution, developed by Balluff, includes a base unit with built-in software. The device offers the possibility to collect and evaluate large amounts of data in a transparent and configurable manner, which cannot be done in a PLC, for example. CMTK collects in-

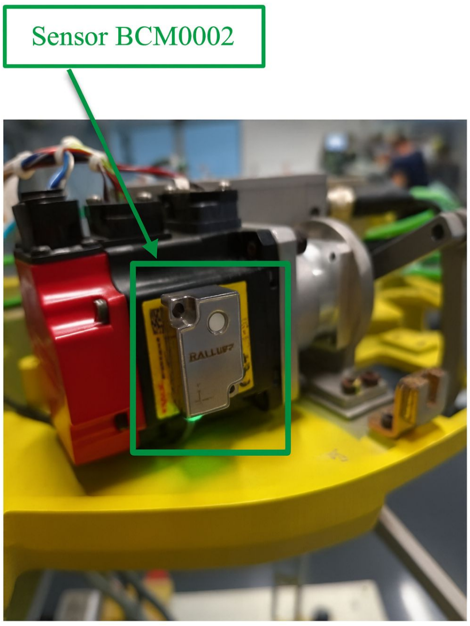

Fig. 2. BCM0002 sensor mounted onto one of the axes of an industrial robot

formation from sensors via IO-Link protocol and then processes it. The base unit is equipped with four IO-Link ports, two LAN1 and LAN2 sockets, a USB-A port and an SD card slot. Thanks to the built-in software, it does not require programming. After assigning an appropriate IP address, the configuration is done via a web server, from where you can go directly to applications supporting condition monitoring, used e.g. to visualize collected data (Grafana). Sensors that monitor the status are connected to the IO-Link ports. The LAN sockets, on the other hand, enable communication with network devices via RJ45 cables. CMTK offers various configuration modes for its network sockets [24]. The device can operate as a: DHCP SERVER – when it acts as a simplified DHCP server, as it can assign dynamic IP addresses to other devices, e.g. computers that connect to it. It is worth noting, however, that this functionality is limited: the device does not allow for the setting of a specific address pool or advanced options typical of full DHCP servers. Alternatively, in DHCP mode, the CMTK CLIENT itself requests an IP address from a DHCP server in the network. It is also possible to assign a static IP address to this component. Figure 3 shows a general view of the components [25].

Fig. 3. Components of CMTK [25]

2.4. Condition monitoring – system integration

The project involved creating a position to monitor the condition of industrial robot joints. Data were collected using a FANUC M-1iA 1H parallel robot with an R-30iB Mate Open Air controller. The manipulator was equipped with three axes, its maximum speed is up to 4000 mm/s, and the maximum lifting capacity is 1 kg. The shape of the workspace is a combination of a cuboid with a base measuring 280×280 mm, and a cone tapering downwards and cut at the end. The total height of the workspace is 100 mm. The task of the robot was to perform a pick and place process. The procedure was carried out continuously – the program never ended. In each cycle, the robot moved eighteen elements at the following speeds: 100 mm/s, 1000 mm/s, 2000 mm/s, 3000 mm/s, 4000 mm/s – this movement formed the basis for the collected data. After each of the first nine elements had been moved, the robot took a 4-second break. The last 9 elements, on the other hand, were moved without interruption at maximum speed. After the cycle was completed, the robot paused for 10 seconds and then restarted the process from the beginning. This infinite process was used to generate data. Vibrations and temperature from the joints were collected by BCM0002 sensors mounted onto each of the robot's axes. Then, using the IO-Link protocol, the data were transferred to CMTK, which was responsible for processing and transferring them to the Grafana application. This is an open-source solution for the graphical visualization of collected data. It allows you to create charts, tables, heat maps and other visualizations.

It supports many types of data, from numerical to temporal. Grafana allows you to set alert rules based on data monitored in real time. It sends notifications via e-mail, Slack, PagerDuty and other channels. Users can view, filter and analyze data on dynamic dashboards. Grafana offers many plugins that extend its functionality, e.g. with new chart types. The fourth CMTK port was occupied by a flow sensor that monitored the amount of air flowing through the robot's suction nozzle. Figures 4 and 5 show the delta-type FANUC M-1iA 1H robot and a view of the robot's joints with the BCM0002 sensors mounted. The blue frames indicate which robot joint a given BCM sensor was attached to, connected to a specific CMTK port.

Figure 6 shows the interconnected network components used in the integrated workstation. The router is connected to the internet, and the condition monitoring toolkit is located in the subnetwork it creates. The first three octets of the IP address

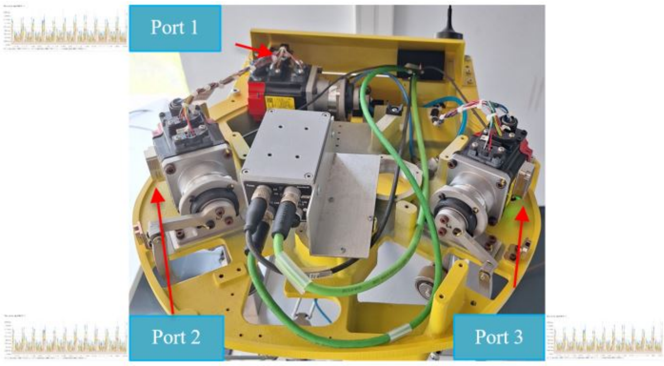

Fig. 4. View of the robot's joints with attached BCM0002 sensors

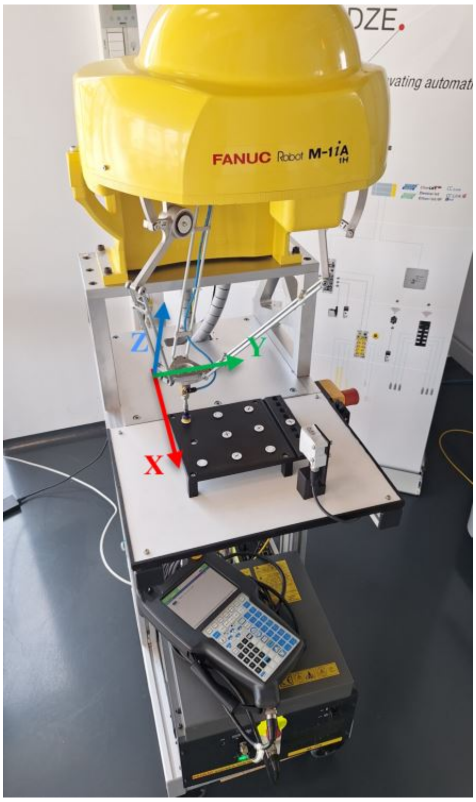

Fig. 5. Delta-type FANUC M-1iA 1H robot

of the router and CMTK are identical, which enables them to communicate due to the subnet mask 255.255.255.0. All devices communicate via Ethernet/IP protocol – they are connected via an RJ45 cable.

Fig. 6. Network view of integrated system

3. RESULTS

The following section is dedicated to the discussion of tests carried out on the integrated workstation. They were based on the analysis of the transparency of the displayed data during the execution of actions by the manipulator. The BCM vibration velocity sensor determines this based on the acceleration, which is measured by an accelerometer. Signal integration is performed within the sensor unit, and the resulting speed signal is transmitted to the graphical environment, where it is visualized in graphs. This setup represents, to our knowledge, the first documented instance of continuous industrial operation combining a FANUC M-1iA robot, Balluff's CMTK and Grafana-based visualization. A work cycle of the robot is understood as the execution of one entire process of placing pucks on the board and putting them back into the warehouse. One cycle, on the other hand, covers one transfer of a specific element to the board. During the tests, program corrections were introduced to make the information displayed in the Grafana application clearer. These included lengthening the intervals between robot work cycles and increasing the differences in speeds during the execution of an individual cycle. There were also minor adjustments to the position of some points – to fully minimize the risk of the manipulator colliding during its long and uninterrupted operation. The robot then continuously ran the program for several days. This extended runtime allowed for a robust assessment of real-time vibration feedback and system response to varying kinematic profiles, illustrating the practical benefits of the setup in early fault detection and runtime condition monitoring. As a result of these actions, multiple data were obtained, some of which is presented below.

During one cycle, the manipulator moves at the following speeds:

- Cycle 1 – 100 mm/s,
- Cycle 2 – 1000 mm/s,
- Cycle 3 – 1000 mm/s,
- Cycle 4 – 100 mm/s,
- Cycle 5 – 2000m m/s,
- Cycle 6 – 100 mms/,
- Cycle 7 – 4000 mm/s,
- Cycle 8 – 100 mm/s,
- Cycle 9 – 3000 mm/s,
- Putting disks into storage – 4000 mm/s.

Each of the cycles has been visualized in Fig. 7.

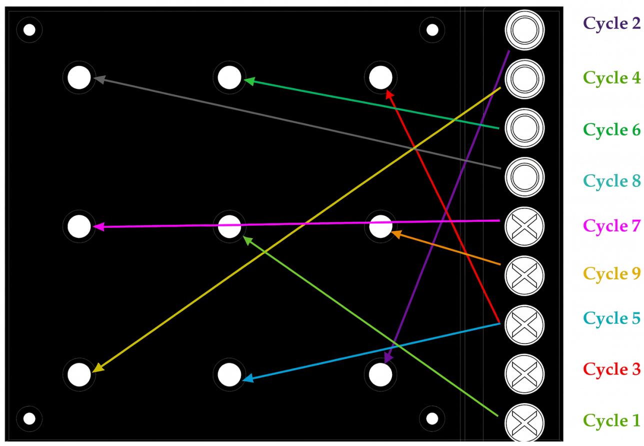

Fig. 7. Visualization of the robot's cycles

Figures 8–10 show the combination of three graphs of the vibration velocity of each robot axis as a function of time (each graph represents one joint of the manipulator). Since the BCM0002 sensor measures vibration velocity in three axes, there are three functions in each graph. Each color of data represents vibrations in a different axis (X, Y, Z), as described in the legend. The domain of the functions covers two robot duty cycles – one of them is marked in Fig. 8. Each sensor measures the vibrations in a specific time window and then averages the measurements, which corresponds to one sample in the graph.

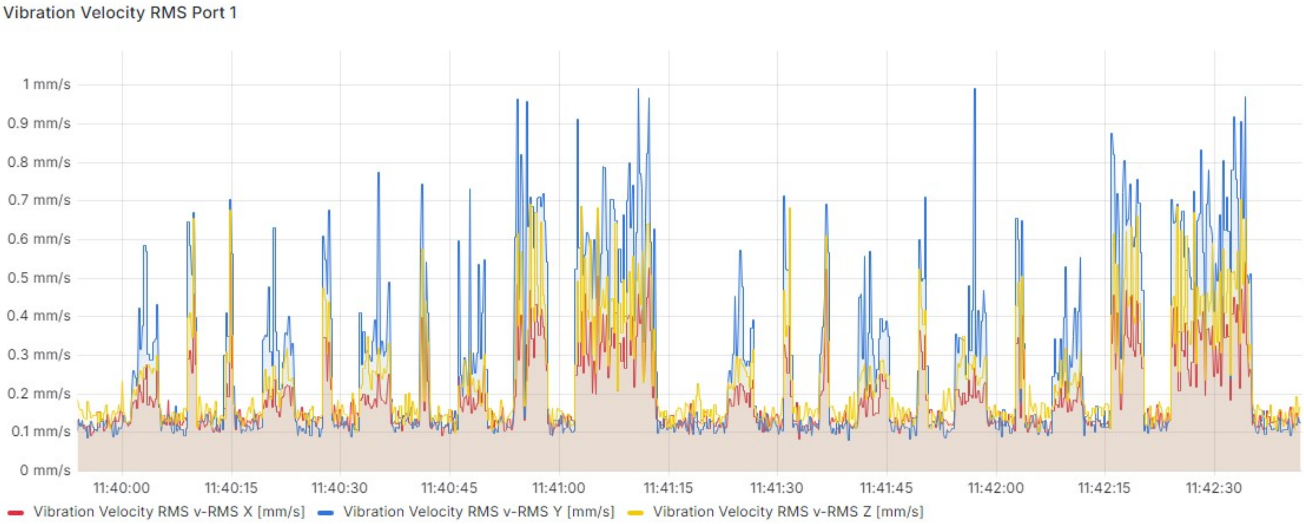

Fig. 8. Example of velocity vibration (port 1)

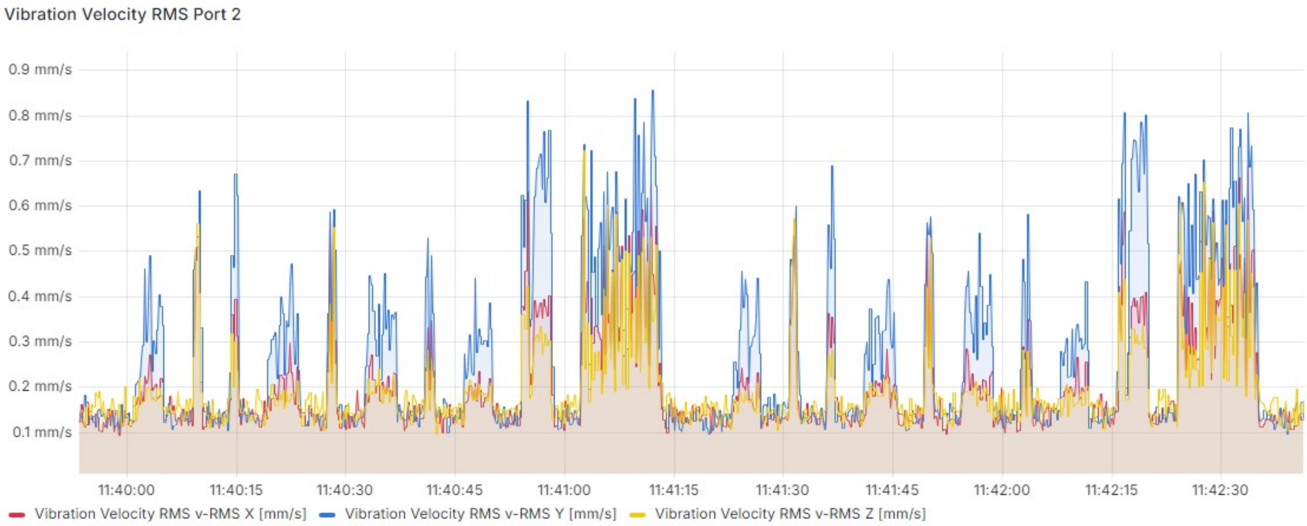

Fig. 9. Example of velocity vibration (port 2)

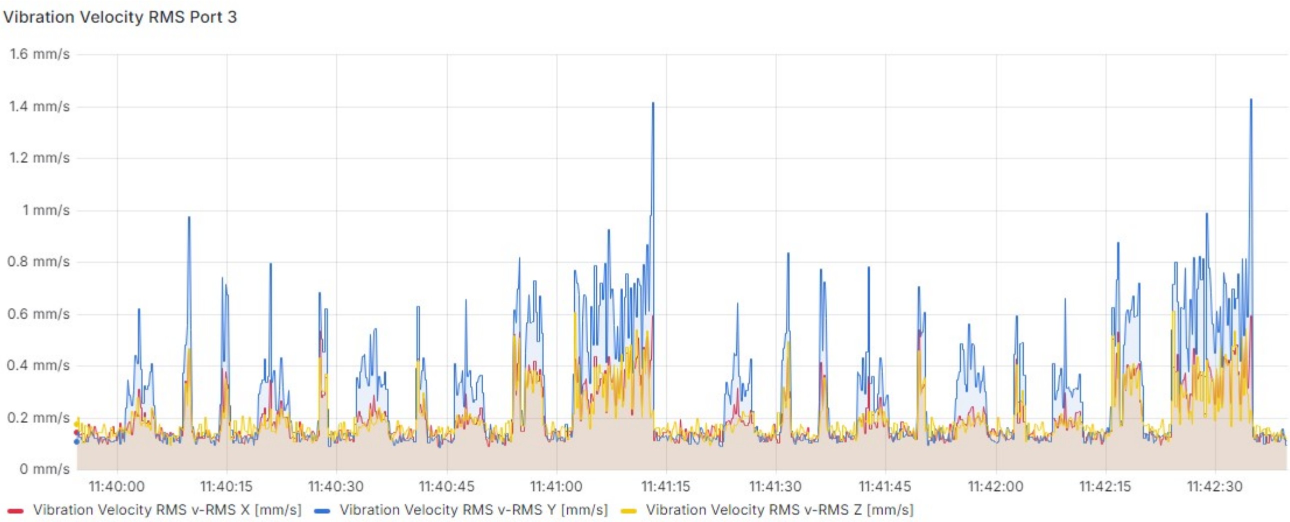

Fig. 10. Example of velocity vibration (port 3)

Figures 11–13 show the vibration velocity characteristics at port 3 CMTK (reference of ports to the robot axes – Fig. 4) distributed into three separate graphs. Each movement of the robot can be distinguished by the following characteristics – for the first nine cycles, the manipulator placed discs on the board. The area after the ninth beat shows the process of the robot putting the discs into storage; these operations are performed without interruption and at a speed of 4000 mm/s. In the ninth cycle before putting the disk away, the effector performed three large circles in the air, extending over the entire working area. This was to introduce circular interpolation into the process. This type of movement is visible on each of the characteristics and marked with a black frame in Fig. 10.

Based on the above characteristics, it can be concluded that the vibration speed depends on the speed at which the robot moves and on the type of movement. The shapes of each of the characteristics for all ports are similar. Only the graph from port three is scaled due to the last recorded speed value on the Y axis, which deviates from the other data. This may be due to the last movement of the robot, which is carried out between two extreme points of the workspace and is performed at a speed set in the registry to 4000 mm/s. The longer the path of the effector, the higher the speed it reaches, approaching the set value. The high-speed forces more abrupt braking, which significantly increases the level of vibration in the system. A comparison of the characteristics shows that the highest vibrations in all axes occur during the last disc placement. The analysis of the graphs also reveals that the higher the speed of movement in a given cycle, the shorter the duration of the cycle, resulting in short-lived but intense vibrations. The smallest vibrations were recorded in the X-axis because the robot covered the shortest distances along this axis. With a time interval of 4 seconds between cycles and 10 seconds between cycles, it is easy to localize the individual intervals in the diagram. A failure of the robot axis or a collision could be recognized by higher and non-cyclical vibration frequencies.

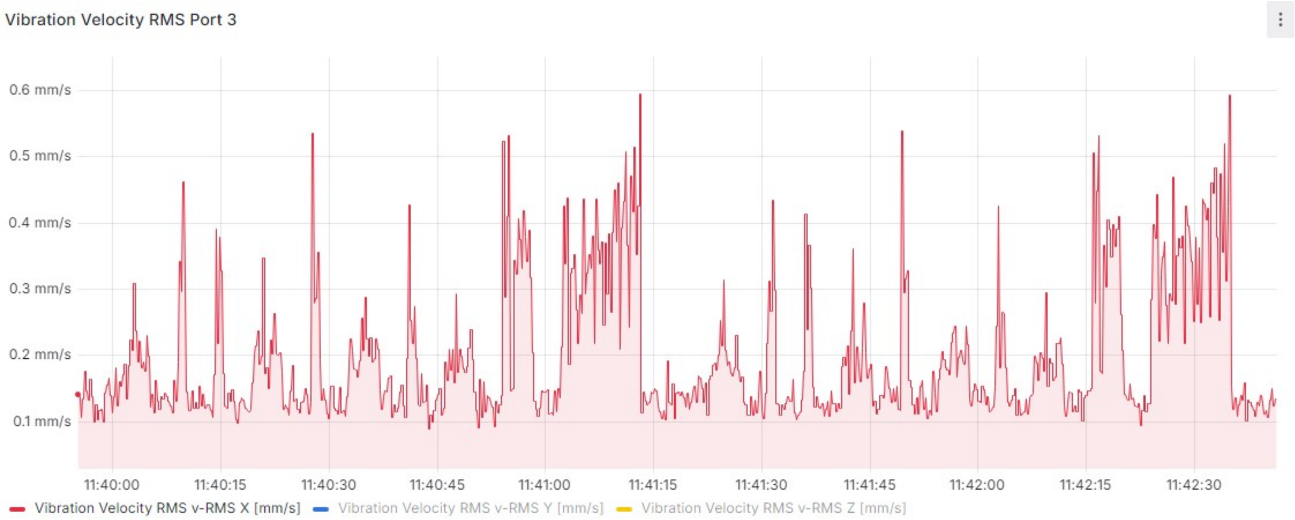

Fig. 11. Vibration velocity of the robot axis corresponding to port 3 (X direction)

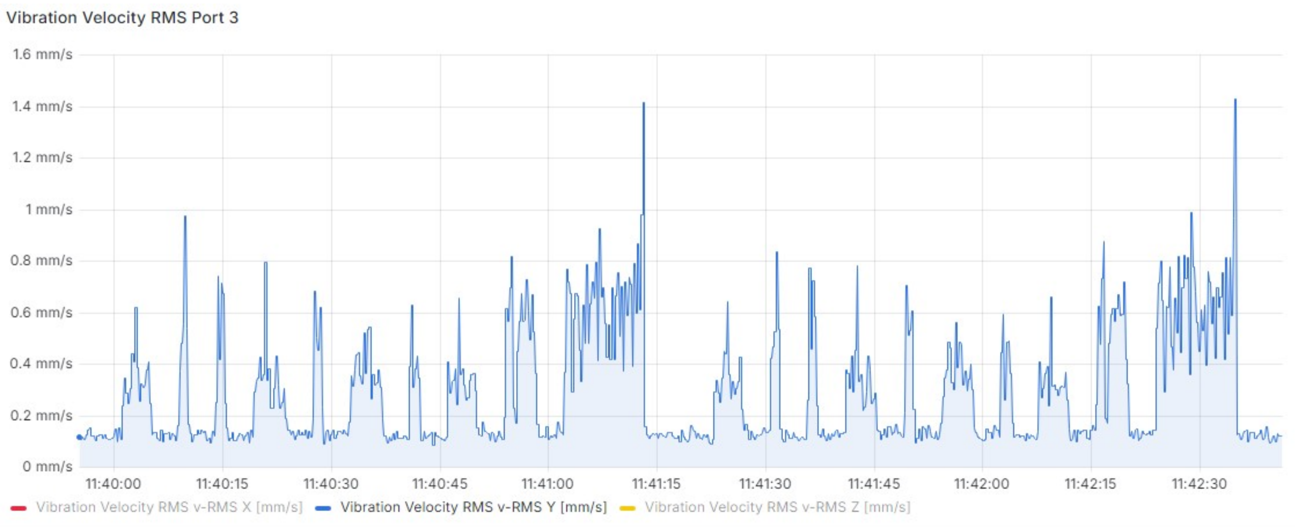

Fig. 12. Vibration velocity of the robot axis corresponding to port 3 (Y direction)

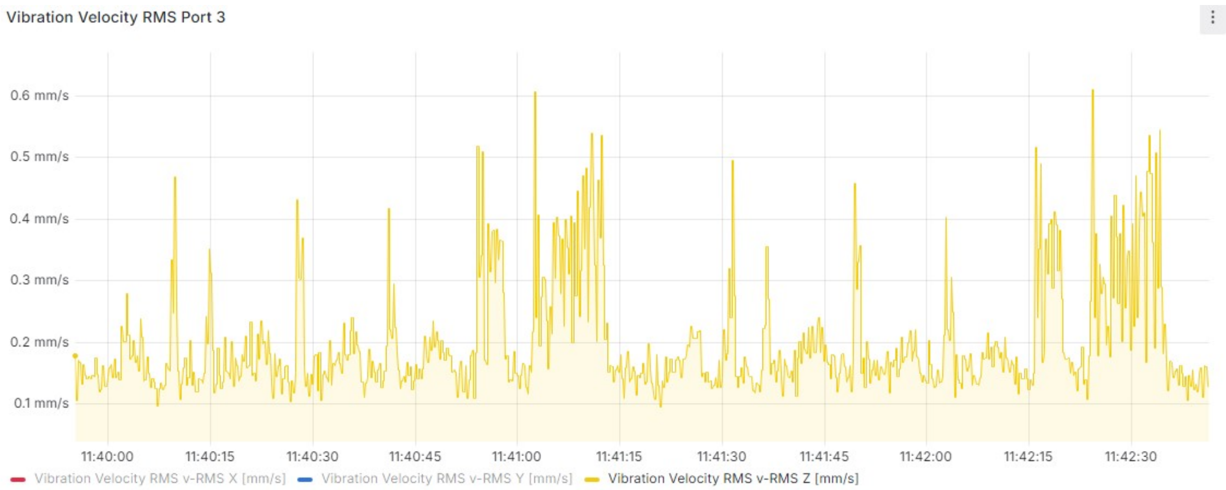

Fig. 13. Vibration velocity of the robot axis corresponding to port 3 (Z direction)

4. CONCLUSIONS

As part of this work, a workstation for monitoring the wear of the joints of the FANUC M-1iA 1H parallel robot was designed, integrated and tested. All stages were successfully completed. The manipulator was restored to full working order and programmed, and all components ensuring its proper operation were successfully integrated. The electrical components responsible for connecting the robot to the network and powering all additional elements were correctly connected. All network devices were correctly connected, enabling the processing and display of the collected data. In the last stage, a clear graphical presentation of the data was created in the Grafana environment. In contrast to many existing IIoT-based diagnostic systems that focus on either hardware-level sensing or post-process data analytics, this work demonstrates a fully integrated and operational industrial diagnostic loop – capturing live data via CMTK, visualizing it through Grafana, and allowing human operators to identify anomalies in real time. The tests carried out consisted of continuous operation of the station for several days. During this time, the collected data were analyzed on an ongoing basis. The robot executed the program correctly and without collisions, even over a long period of time. The vibration graphs show the repeatability of the cycles. If the manipulator works at higher speeds, higher vibrations are visible, and at lower speeds they are lower, which proves that the sensors are correctly mounted and integrated. The temperature of the joints stabilized at a certain level, which indicates the absence of a failure. In the event of a robot joint failure or collision, non-cyclical vibration frequencies, increased temperature or changes in current consumption would be visible in the graphs. Balluff will continue to further develop the station utilized herein by creating a web interface. It will be accessible via the WAN IP address of the router and, after logging in, users will be able to view the currently collected data. These data will be accessible from anywhere in the world, which is in line with the idea of machine and device condition monitoring technology and the principles of Industry 4.0. At a further stage, it is planned to develop the workstation and extend the project to include software that analyzes the information provided, so that the user is not burdened with the analysis of the displayed data, but can have direct insight into the condition of the robot's joints. Balluff's condition monitoring toolkit (CMTK) offers a compact and integrated solution for monitoring key machine health parameters like vibration, temperature and humidity. Its major advantage lies in the ease of deployment – featuring IO-Link connectivity and built-in data processing, it allows for seamless integration into industrial automation systems. Unlike many third-party systems, CMTK requires no external software or controllers, as it can process and transmit condition data directly to PLCs or cloud platforms. The system is designed for harsh industrial environments, providing robust housing and reliable operation under challenging conditions. While alternatives like the IFM VVB020 [26] or Analog Devices Voyager [27] kits exist, they often require additional configuration or infrastructure, making Balluff's CMTK much more flexible for plug-and-play industrial monitoring. The system presented contributes to broader smart manufacturing objectives by enabling predictive maintenance through real-time condition monitoring, which helps to anticipate component degradation before failures occur. Its continuous data acquisition and visualization capabilities improve uptime optimization by allowing early detection of anomalies and rapid response. Moreover, the modular and non-invasive nature of the CMTK toolkit makes the solution scalable across different robot models and industrial environments, supporting flexible deployment in diverse automation scenarios. Despite its contributions, the current system also has several limitations. Tests were performed on a single robot platform (FANUC M-1iA), and no induced fault scenarios were implemented to validate failure response in practice.

Future work may explore deployment in collaborative or mobile robotic systems, where dynamic environments present more complex monitoring challenges and safety considerations.

The solution's engineering relevance is notable: low detection latency, ease of deployment (due to IO-Link and no external software), and its cost-effective nature make it highly attractive for small and medium-sized enterprises (SMEs) seeking scalable condition monitoring without major infrastructure investments.

ACKNOWLEDGEMENTS

The authors would like to express their gratitude to Balluff Poland for supporting students and academic staff in development of automation technologies.

FUNDING

This article has been supported by the European Funds for Social Development (FERS) program and the Support for Alliances of European Universities NAWA program numbered BPI/WUE/2024/1/00031/DEC/1.

REFERENCES

[1] T. Barszcz, *Vibration-Based Condition Monitoring of Wind Turbines*. Cham, Switzerland: Springer, 2019, doi: 10.1007/978-3-030-05971-2.

[2] R.R. Rabi, M. Vailati, and G. Monti, "Effectiveness of vibration-based techniques for damage localization and lifetime prediction in structural health monitoring of bridges: A comprehensive review," *Buildings*, vol. 14, no. 4, p. 1183, Apr. 2024, doi: 10.3390/buildings14041183.

[3] S.S. Saidin, A. Jamadin, S.A. Kudus, N.M. Amin, and M.A. Anuar, "An overview: The application of vibration-based techniques in bridge structural health monitoring," *Int. J. Concr. Struct. Mater.*, vol. 16, p. 69, 2022, doi: 10.1186/s40069-022-00557-1.

[4] T. Singh, S. Sehgal, C. Prakash, and S. Dixit, "Real-time structural health monitoring and damage identification using frequency response functions along with finite element model updating technique," *Sensors*, vol. 22, no. 12, p. 4546, Jun. 2022, doi: 10.3390/s22124546.

[5] F. Min, Y. Cai, Y. She, G. Wang, and D. Li, "Robot collisions classification based on variational mode decomposition of vibration measurements," *IEEE Trans. Instrum. Meas.*, vol. 73, 2024, p. 3385848, doi: 10.1109/TIM.2024.3385848.

[6] C. Nentwich and G. Reinhart, "Towards data acquisition for predictive maintenance of industrial robots," *Procedia CIRP*, vol. 104, pp. 971–976, 2021, doi: 10.1016/j.procir.2021.11.011.

[7] H.A. Raja, T. Vaimann, A. Rassõlkin, A. Kallaste, and A. Belahcen, "IoT based tools for data acquisition in electrical machines and robotics," in *Proc. IEEE 19th Int. Power Electron. Motion Control Conf. (PEMC)*, Gliwice, Poland, 2021, pp. 650–655, doi: 10.1109/PEMC48073.2021.9432553.

[8] H. Han, D. Shi, L. Gu, N. Wei, and F. Gu, "Modelling and vibration signal analysis for condition monitoring of industrial robots," in *Proc. IncoME-VI and TEPEN 2021, Mechanisms and Machine Science*, vol. 111, Cham, Switzerland: Springer, 2021, pp. 731–741, doi: 10.1007/978-3-030-99075-6_71.

[9] U. Hassan, K.K. Panduru, and J. Walsh, "An in-depth study of vibration sensors for condition monitoring," *Sensors*, vol. 24, no. 3, p. 740, Jan. 2024, doi: 10.3390/s24030740.

[10] H. Lu, X. Zhao, B. Tao, and Z. Yin, "Online process monitoring based on vibration-surface quality map for robotic grinding," *IEEE/ASME Trans. Mechatron.*, vol. 25, no. 6, pp. 2620–2631, Dec. 2020, doi: 10.1109/TMECH.2020.2996939.

[11] H. Han, Y. Lin, L. Gu, Y. Xu, and F. Gu, "Vibration analysis based condition monitoring for industrial robots," in *Proc. IncoME-V & CEPE Net-2020, Mechanisms and Machine Science*, vol. 105, Cham, Switzerland: Springer, 2020, pp. 155–165, doi: 10.1007/978-3-030-75793-9_19.

[12] N.A. Ismail, M.I.S. Ismail, A. As'arry, M.K. Anuar, and M. Ariffin, "Vibration analysis of forming tool and thin sheet metal in robot-based single point incremental sheet forming," *Test Eng. Manage.*, vol. 83, pp. 12873–12884, 2020.

[13] Z. Rao, B. Feng, L. Liu, and Y. Wang, "Equipment condition monitoring system based on LabVIEW," in *Adv. Manuf. Automat. VII. IWAMA 2017, Lecture Notes in Electrical Engineering*, vol. 451, Cham, Switzerland: Springer, 2018, pp. 485–494, doi: 10.1007/978-981-10-5768-7_56.

[14] H. Hasani, F. Freddi, R. Piazza, and F. Ceruffi, "A wireless data acquisition system based on MEMS accelerometers for operational modal analysis of bridges," *Sensors*, vol. 24, no. 7, p. 2121, Apr. 2024, doi: 10.3390/s24072121.

[15] R.J. Stephen, T. Thangeswari, S. Palani, and D. Dinakaran, "Condition monitoring in drilling operation based on vibration signals," *Int. J. Recent Technol. Eng.*, vol. 8, no. 3, pp. 7664–7668, Sep. 2019, doi: 10.35940/ijrte.C4416.098319.

[16] X. Zhao, H. Lu, W. Yu, B. Tao, and H. Ding, "Robotic grinding process monitoring by vibration signal based on LSTM method," *IEEE Trans. Instrum. Meas.*, vol. 71, p. 3210976, 2022, doi: 10.1109/TIM.2022.3210976.

[17] H. Badkoobehhezaveh, R. Fotouhi, Q. Zhang, and D. Bitner, "Vibration analysis of a 5-DOF long-reach robotic arm," *Vibration*, vol. 5, no. 3, pp. 395–413, 2022, doi: 10.3390/vibration5030034.

[18] S. Halder and K. Afsari, "Robots in inspection and monitoring of buildings and infrastructure: A systematic review," *Appl. Sci.*, vol. 13, no. 4, p. 2304, Feb. 2023, doi: 10.3390/app13042304.

[19] T. Brogårdh, "Present and future robot control development – An industrial perspective," *Annu. Rev. Control*, vol. 31, no. 1, pp. 69–79, 2007, doi: 10.1016/j.arcontrol.2007.01.002.

[20] C. Nentwich and R. Daub, "Comparison of data sources for robot gear condition monitoring," *Procedia CIRP*, vol. 107, pp. 554–559, 2022, doi: 10.1016/j.procir.2022.04.051.

[21] C. Yuan, B. Xiong, X. Li, X. Sang, and Q. Kong, "A novel intelligent inspection robot with deep stereo vision for three-dimensional concrete damage detection and quantification," *Struct. Health Monit.*, vol. 21, no. 3, pp. 1033–1048, 2021, doi: 10.1177/14759217211010238.

[22] A. Frej, X. Chiementin, C. Fakher, F. Bolaers, and M. Haddar, "Dynamic modeling and vibration analysis for defect identification of single-stage gearboxes in the joints of industrial robots with six DOF," *Proc. Inst. Mech. Eng., Part C: J. Mech. Eng. Sci.*, vol. 237, no. 19, pp. 3923–3939, 2023, doi: 10.1177/09544062231152347.

[23] H. Han, Y. Lin, L. Gu, Y. Xu, and F. Gu, "Vibration analysis based condition monitoring for industrial robots," in *Proc. IncoME-V & CEPE Net-2020*, Cham, Switzerland: Springer, Oct. 2020, pp. 155–165, doi: 10.1007/978-3-030-75793-9_19.

[24] Balluff GmbH, "BCM R15E-001-DI00-01,5-S4 – Product data sheet," 2025.

[25] Balluff GmbH, "BAV MA-NC-00025-01 – Product data sheet," 2025.

[26] "Vibration sensor VVB020, vibration IO-link switch", Product data sheet, 2025.

[27] Analog Devices, "Voyager 4 – Wireless motor monitoring development platform – User guide." [Online]. Available: https://wiki.analog.com/resources/eval/user-guides/voyager4 (Accessed: Jun. 10, 2025).